THE APPLICATION OF THE LOG-LINEAR MODEL IN THE FISHING INDUSTRY

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by

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Abstract

This thesis is specifically related to the fishing industry. In the first part of this thesis, literature review is done on estimating the size-selectivity of gillnet. There are currently five widely-used methodologies about the size-selectivity of gillnet. After briefly describing all of them, respective examples about these five theories are given. The purpose of the first part is to clarify some useful statistical procedures for the problem encountered by fishing industries.

In the second part of this thesis, the approach by Millar and Hoslt (1997) is employed and compared with the log-linear model. Using the data from fleet EW and fleet JV, it is found that the normal scale model yields the smallest deviance for JV, but not significantly smaller than that from the normal location model. For EW, the normal location model produces the smallest deviance, but not significantly smaller than the normal scale model. For both data sets, the Lognormal model yields the largest deviance.

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Chapter 1

Introduction

Fishing communities across Canada gain social and economic value from using our oceans resources. The fundamental objective of any responsible fishing operation is to maximize returns to the operator with minimum influences on the fish populations and the environment. A 2003 assessment of turbot off eastern Newfoundland and Labrador indicated that the stock is expected to decline in abundance. A rebuilding plan that includes severe harvest reductions has therefore been put in place, beginning in 2004. Knowledge of the size-selectivity of commercial fishing gears is crucial to management of a fishery for purposes of maximizing yield and protecting juvenile fish (Gulland, 1983; Wileman *et al.*, 1996). Moreover, fishing gears may be used as research tools for monitoring the length distribution of the stock by using the mesh size-selectivity of the gears to adjust the length distribution of the catches. Gillnets selectivity is the focus of this thesis.

Selective fishing is defined as the ability to avoid non-target fish, invertebrates, seabirds, and marine mammals or if encountered, to release them alive and unharmed (Fisheries and Oceans Canada 2001). Research in fishing gear selectivity is a very important area for fishery management. For commercial fishing activities carried

out at sea, fishing gear should be designed to allow undersized fish to escape while the target fish is retained. In this dissertation, we shall assume turbot is the target species of fish. Turbot are found in deep waters from the Arctic south to Georges Bank. In Canada, the fishery is mostly confined to the deep bays of Newfoundland and Labrador, Baffin Island, and the Gulf of St. Lawrence. Traditionally a line trawl fishery, gillnets are also used both inshore and offshore, while otter trawls are used mainly in offshore fisheries. For simplicity, we will not consider other factors such as by-catches.

Mode of fishing influences the selectivity of fishing as well as the choice of measurement technique. Fishing gear can be classified into two groups, mobile and static. Mobile gear, as the name implies, is actively moved through the water, catching fish as they are encountered. In contrast, static gear remains still and it is the fish that move and expose to the gear.

1.1 Mobile Gear

Trawling is recognized as an important harvesting technology in terms of landings. Therefore, the main analysis discussed under mobile gear will focus on trawling. The term "trawl" is used here to represent a wide range of gear variations including otter trawls, mid-water trawls, beam trawls and so on. In simplified terms, a trawl is a cone-shaped net which is made of a series of panels of netting that are towed along the seabed or midway through the water column to capture fish.

1.1.1 Capture Process

As the trawl is towed along, fish are herded into the path of the net and are overtaken by it. Once the fish are herded in the net, they eventually fall back to be held in

the end part of the net- the codend. As a conventional trawl codend fills with fish, the meshes along its length tend to close. The reason is that the increasing drag of the catch creates more tension in the net. After a period of towing, the trawl is removed from the water, the codend is brought back to the vessel and the catch from the codend recovered.

1.1.2 Factors Influencing the Selectivity of Trawl

This capture process reveals the importance of mesh shape and size, towing time (Liangzhuang Ma, 2004) towing speed, codend design and other factors (Measurement of Fishing Gear Selectivity, 1995) in the selectivity of gear(Liangzhuang Ma, 2004). Heightened environmental concern, in recent years, has resulted in many design and operational changes which aimed at improving selectivity.

The mesh size is defined as the distance between opposite corners of the mesh when it is fully stretched. Mesh size and shape have been widely used as the traditional means of affecting selectivity in trawls. Usually, the larger the mesh size, the higher the probability of small fish escaping through the gaps in the netting. In practice, many other factors affect the theoretical impact of mesh size in determining the escapement of undersized fish from trawls. These factors include:

- trawl geometry
- ground gear
- pre-selection devices
- lastridge ropes
- separator panels

- grids/grates

Research has shown that under certain conditions, mesh shape has a greater impact than mesh size. At high towing speeds, for example, diamond-shaped mesh openings tend to become elongated and can theoretically close altogether, regardless of their sizes. A similar effect is experienced when catch rates are high and the codend becomes full. In some instances, mesh configuration (size and shape) is ineffective in achieving improved selectivity (Measurement of Fishing Gear Selectivity, 1995).

Towing time has a great impact on affecting selectivity in trawls. Although prolonged towing time destroys some fish, it will increase the retention rate of the undersized fish. The longer the gear stays in the water, the more time the undersized fish can escape from the gear. If the gear stays in the water for too long until almost all the mesh is blocked in the codend component, there will be no chance for those undersized fish to escape (Liangzhuang Ma, 2004).

As with most fishing gear, environmental and tidal conditions play an important role in trawl performance. Increasingly, it is held that differences in the active and passive behaviour of intermixed species can be exploited to achieve selectivity prior to fish entering the trawl. In principle, certain species and sizes of fish are more apt to avoid trawl components which are highly visible in appearance. This means that selectivity can be affected not only by the visual appearance of gear but also by the amount of light available to make it visible (Liangzhuang Ma, 2004).

1.2 Static Gear

Static gear is often associated with bait or food stimulus which attracts fish and encouraging them to move toward the gear and become captured. Some fixed gears, however, such as gillnets and cod traps operate without baits, and it is the natural

daily movement of fish that precipitates capture in these gears. Capture, in this instance, is usually assisted by water movements such as tidal and other currents in the sea or stream flow in fresh water (Measurement of Fishing Gear Selectivity, 1995).

A gillnet is made up of a long rectangular web of netting which is set in the water to form a vertical wall. A buoyant headline and a weighted groundrope ensure that the net wall remains in a vertical position. Spatial orientation is controlled by a variety of methods depending on the type of fishing desired. If the gillnet is being fished on the bottom, one or both ends of the net are secured to the ocean floor to ensure that the spatial orientation is maintained (Measurement of Fishing Gear Selectivity, 1995).

To accommodate fishing on the surface or in midwater, the buoyancy of the headline and the weight of the groundrope are adjusted to allow the wall effect of the netting to be maintained. A surface fishing net, independent of a fishing vessel, may be attached to land at one end and have an anchor at the other or it may have anchors at both ends. If the net remains attached to a fishing vessel, it is usually referred to as a drift net and can be many kilometers in length (Measurement of Fishing Gear Selectivity, 1995).

1.2.1 Capture Process

Fish are caught in a gillnet in one of three ways: (a) wedging , a fish held tight around the body by a mesh; (b) gilling , a fish that enters the net is too large to pass through, and is prevented from retreating by twine that catches the fish behind the gill; and (c) tangling , a fish that has not necessarily penetrated a mesh is caught in the net by teeth, maxillaries or other projections.

There are many factors which may affect the selectivity of gillnet fishing. Mesh

size is considered to be the most important. Other factors include the environment in which the gear is operating and characteristics of the gear such as twine and gear design. Our study will focus on the factor of mesh size.

Capture by gilling, wedging and tangling are dependent on the shape of particular species of fish encountered. Therefore, gillnets are size and species selective. The processes of "wedging" and "gilling" are the most common ways by which a fish becomes meshed in a gillnet. "Wedging" is a function of the maximum girth of a given species and length of fish. "Gilling" is a function of the head girth. The smallest fish caught has a maximum girth equal to the perimeter of the mesh; the largest fish caught has a head girth equal to the perimeter of the mesh. Most fish between these two sizes would be caught. There is an optimum size at which a fish is most likely to be held for sure, being unable to escape. Fish below and above this optimum size, but within the capture range, are less likely to be captured. Under these conditions, the size selection curve for a gillnet is usually a symmetrical bell-shaped curve in which the mode (peak) corresponds to the optimum length and the curve falls away on each side to zero. Therefore, the knowledge of the size-selectivity is crucial for purposes of maximizing yield and protecting juvenile fish.

1.2.2 Factors Influencing the Selectivity of Gillnet

Twine material, gear construction, and mesh size are all important factors which can affect the fish capture process and thus the selectivity of the gear. Design and construction of nets are aimed at minimizing visibility and maximizing elasticity and strength of the twine. Good strength is necessary to avoid damage as fish attempt to free themselves or as the gear is recovered. The construction, flotation, and weighting of the gear affect net behavior in the water which in turn affect both the selectivity

and the efficiency of fishing. The headline and groundropes and their relative magnitudes are important in ensuring that the net shape and fishing power are maintained. Similarly, the hanging ratio of the web on the headline and the attachment ratio on the groundline can all influence selectivity.

The mesh location, mesh amount, and mesh orientation of fishing gear can effectively pre-select the fish that will be encountered by the net. The soak time before retrieval can affect the efficiency and sometimes the selectivity of a gillnet. The net may become dirty with slub and detritus as the soak time increases, resulting in increased visibility and decreased efficiency. As fish accumulate, the selectivity of the gear may decrease resulting in the capture of unwanted species and sizes of fish or selectivity may increase due to fish being attracted to fish caught in the net (Measurement of Fishing Gear Selectivity, 1995).

In this thesis, we will focus on gillnet and the factor of mesh size.

Chapter 2

Literature Review

Gillnet selectivity fits the broad definition of selectivity (the ratio of the number of fish caught by the experimental net to the number of fish exposed to the gear for a given species and size of fish). The number of fish caught by the experimental net is readily obtained; however, the number of fish exposed to the gear is not always easily obtained. What follows is a description of various methods used to determine gillnet selectivity and partial research about the size selectivity of gillnet.

2.1 Population Known

If the size distribution of the fish population is known, the selectivity of gillnets can be calculated by the following method.

$$selectivity = \frac{a}{b} \tag{2.1}$$

where a is the number of fish caught and b is the number of fish exposed to the gear.

This method is usually the most reliable estimate available. However, it is not commonly used as the size population of fishes is difficult to predict. This method is used predominately to check on the validity of the assumptions utilized in other

methods. If the unknown population is estimated, then the assumptions must be considered in the analysis. With regard to the known population, generally any assumptions made in calculating the estimate will govern both the accuracy and precision of the estimates (Measurement of Fishing Gear Selectivity, 1995).

2.2 Comparison with a Gear of Known Selectivity

If the size distribution of the fish population is known from results of fishing with a net of known selectivity, gillnet selectivity can be estimated by comparing the catch of the experimental gear with the population estimate from the net of known selectivity. When possible, gillnet catches should be compared with a relatively non-selective gear such as a small- meshed codend. This comparison assumes that the catch of the non-selective gear fully reflects the size and species distribution of the fish population exposed to the gear (Measurement of Fishing Gear Selectivity, 1995).

2.3 Comparison of Fish Caught by Gillnets with Different Sized Meshes

Using this method, we calculate selectivity curves by comparing the catches of one size class of fish from nets of several sizes (also known as "type B" selectivity curves). Methods based on this concept do not require the size distribution of the fish population, but instead, rely on assumptions about the shape and height of selectivity curves. Initially, it is necessary to estimate the shape of the curve showing the selectivity of the length group at different mesh sizes. All mesh sizes, when fished with the same effort, are equally likely to be encountered by fish and thus the catches are proportional to the selectivities. Plotting the catches against the mesh sizes will generate

a type B selectivity curve for a given size class. The same can be done for the other major size classes and all the curves. So we can composite three-dimensional display with selectivity presented as a function of both mesh size and fish length. It should be noted that this method has received little attention since the 1960s (Measurement of Fishing Gear Selectivity, 1995).

2.3.1 Selectivity of Gillnets, Especially to Lake Whitefish, Regier and Robson 1966

Regier and Robson re-examined five methods previously described for estimating the selectivity of gillnets by mesh size, and introduces four more. They used the data on whitefish from South Bay, Manitoulin Island, Ontario (1958-1963) to estimate selectivity characteristics.

The methods considered most reliable yielded estimates of selectivity curves for whitefish resembling the normal probability function with a positive skew. The length at which the mode occurred was a significantly nonlinear function of mesh size, the variance was approximately proportional to the square of the mesh size, and the coefficient of skewness is not related to mesh size.

An implication of these findings is that, for general sampling purposes, standard gangs in which mesh sizes increased in a certain geometric progression would be more efficient than those with mesh sizes in the usual arithmetic progression.

2.3.2 Review of Gillnet Selectivity, Hamley 1975

Hamley reviewed studies on gillnet selectivity; the relevant characteristics of fish and nets, graphical and mathematical representation of selectivity curves, and methods of estimation.

Selectivity depends mainly on fish size and shape and mesh size, but is also affected by the thickness, material, and color of net twine, hanging of net, and method of fishing. The left slopes of selectivity curves represent smaller fish wedged in the meshes; the right slopes, larger fish mainly tangled by head parts. The curves may be very skewed or multimodal for fish that are easily tangled.

The most reliable, though expensive, estimates of gillnet selectivity are by "direct" methods of fishing a population of known size-frequency distribution. The more popular but biased "indirect" estimates compare catches by two or more mesh sizes. Other methods used are prediction from girth measurements and the DeLury method.

2.3.3 A New Method of Estimating Gillnet Selectivity, with An Example for spotted seatrout, Helser *et al* 1991

Helser *et al* (1991) proposed a new method of estimating the selectivity of gillnets. This new method is applied to spotted seatrout (*Cynocion nebulus*) in coastal Louisiana and used to estimate the relative abundance of the various size-classes of fish in the population. Using data on the distribution of fish lengths from the catches of various meshes, a system of m equations and n unknown coefficients is simultaneously solved describing the functional relationship of the moments from an assumed mathematical model across mesh size and size class of fish. The solution to the model is a response surface describing the probability of capture of fish of size-class j in mesh i.

Helser *et al* (1991) suggested that this approach for estimating gillnet selectivity has several advantages over other methods: it is very flexible in terms of choosing a mathematical model which would best represent the data; it take full advantage of the empirical data allowing catch information, n_{ij}, to contribute to the final solution

both as a function of mesh size and size-class; and it offers simplicity and elegance in its overall iterative least squares approach and is tractable in terms of assessing the reliability of the parameters and model used.

2.3.4 Estimating Size Composition and Associated Variances of A Fish Population from Gillnet Selectivity, with An Example for Spotted Seatrout, Helser *et al* 1994

Helser *et al* (1994) presented a method of estimating the corrected size composition and associated variances of a fish population and developed a new method of estimating gillnet selectivity which uses a non-linear iterative least-squares approach. Helser *et al* (1994) applied the selectivity model and variance estimation procedure to the experimental gillnet catches of spotted seatrout from 1988 to 1990 and examined model selection parameters estimates, corrected population size compositions, and their variances.

Helser *et al* (1994) presented a modification to the selectivity equation used in an earlier approach which reduces heterogeneous error variance. Non-linear least-squares parameters are used to estimate the population size composition corrected for the effects of mesh selectivity and a procedure is described to estimate their variances. Likelihood ratio tests indicated that model selection parameter estimates were significantly different between the sexes, suggesting that factors which affect the selection process may differ between the sexes. Corrected size compositions for female and male spotted seatrout population were found to differ substantially from the observed catch frequencies, indicating negative bias for smallest size classes. Variability associated with corrected size composition estimates, as expressed by 95% confidence intervals, indicated that in general, precision associated with those quantities is good.

2.4 Estimating Selectivity by Inference from Girth Measurements

This method does not require size distributions to be obtained from gillnet catches. Instead the selection range, the shape and the modal length are all estimated from girth measurements of the fish. The assumption is made that to be gilled or wedged a fish must be able to pass through the mesh beyond its gilled covers but only as far as its maximum girth will allow. Thus, by ignoring all other means of capture, selectivity can be modeled from measurements of head girth and maximum girth for a given mesh size and species of fish. Under these conditions, the selection range of a net consists of those fish whose maximum girth is larger, and the head girth smaller, than the perimeter of the mesh. The selection range can then be obtained using the relationships among fish length, maximum girth and length versus head girth. The peak of the selection curve can be estimated roughly according to the principle that the girths of the most efficiently caught fish are proportional to the mesh size:

$$\text{Maximum girth} = 1.25 \times \text{mesh perimeter} \tag{2.2}$$

(Measurement of Fishing Gear Selectivity, 1995)

2.5 Estimating Selectivity by Fitting a Pre-determined Distribution

Holt (1963) devised a method of determining gillnet selectivity that allows selectivity curves to be obtained by comparing the catches from two or more gillnets, each of which has a slightly different mesh size but is fished with the same effort. And after that, many researchers developed new methods according to the theory of Holt. These

kind of methods have been proven to be the most popular methods for determining the size-selectivity of gillnets (Measurement of Fishing Gear Selectivity, 1995).

2.5.1 A Method for Determining Gear Selectivity and Its Application, Holt 1963

This method is applied to data for the Fraser River sockeye salmon and it is shown that the gillnet mesh selection curve is approximately normal. Holt showed that it is possible to determine the parameters of a gillnet selection curve from the results of comparative fishing experiments by using only gillnets, provided the general form of the selection curve is known. In this study, Holt build up a body of knowledge about the shapes of selection curves for particular types of gear. The mean of the length selection curve is proportional to the size of the mesh, and the girth of a fish of the mean selection length is approximately equal to the perimeter of the mesh.

2.5.2 Gill Net Mesh Selectivities for Gummy Shark, Mustelus Antacticus Günther, Taken in South-eastern Australian Waters, Kirkwood and Walker 1986

Kirkwood and Walker reviewed existing methods for estimating mesh selectivities, and described a new method to overcome some problems in the existing methods. In this method, an assumed selectivity function is fitted directly to catch data for a number of different mesh sizes, with the parameters of the selectivity function being estimated simultaneously across mesh sizes and length-classes.

The new method is used to estimate selectivities for the gummy shark data in south-eastern Australian water (1973-1976). This new method assumed that the

selectivity function takes the shape of a gamma distribution. Data from 2in and 3in. mesh nets did not satisfy the assumptions of the procedure, but estimates of mesh selectivities were successfully obtained for the 4in - 9in mesh nets.

2.5.3 Simultaneous Determination of Gillnet Selectivity and Population Age-class Distribution for Two Cyprinids, Boy and Crivelli 1988

Boy and Crivelli proposed a new indirect method for estimating gillnet selectivity. This new method is applied to two species of cyprinid caught in Lake Mikri Prespa, North Western Greece (1984-1985). They used the data on the distribution of fish length for each age class plus length distribution for each mesh size to calculate both the selectivities and the proportion of each age class in the population.

Boy and Crivelli made no assumptions concerning the shape of the curves, but they did assume that for each mesh size the maximum selectivity is equal to one. In the case where the number of age classes is greater than the number of different mesh sizes, Boy and Crivelli are conscious of introducing a bias in ignoring certain age classes.

2.5.4 A Method for Estimating Gillnet Selectivity of Walleye(Stizostedion Vitreum Vitreum) in Multimesh Multifilament Gillnets in Lake Erie, and Its Application, Henderson and Wong 1991

Henderson and Wong (1991) described a new method for assessing a systematic component of bias associated with the retention characteristics of multimesh gillnets. This

new method is applied to twelve years (1978-89) of walleye catches. From this data, Henderson and Wong (1991) derive frequency distributions of the ratios of fish girth and mesh perimeter for mesh size.

This method is an indirect method that fits an assumed probability distribution to empirical data. An encounter model based on swimming speed of walleye was used to estimate the probability of walleye encountering gillnets. Adjustments were made to walleye catches for both retention and encounter probabilities.

2.5.5 Estimating the Size-selectivity of Fishing Gear by Conditioning on the Total Catch, Millar 1992

Millar used a conditional maximum likelihood model to estimate the size-selectivity of trawls, gillnets, and hooks when the data are obtained by simultaneous fishing with meshes or hooks of different size and/or shape. Millar used the catch of haddock from an alternate haul study (from Pope et al. 1975, p.48) to apply the method about trawls and used the catch of snapper(*Pristipomoides zonatus*) on two different sizes of circle hook to apply the method about gillnets and hooks.

Size-selectivity is expressed there by the selection curve, $r(l)$, the probability that a fish of length l, if contacting the gear, will be retained (caught). In many other previous selectivity studies, $r(l)$ is fitted either by eye, by heuristic means, or by improper application of generalized linear models. Then it is not possible to make legitimate statistical inference about $r(l)$, or about assessments of the state of the fishery if those assessments use $r(l)$. Millar showed that by conditioning on the total catch, selectivity data can be modeled as binary data, or polytomous data on interval scales. Application of the model to trawl and hook data demonstrates that selection curves can be fitted using generalized linear models, which may require nonstandard

link functions or link functions with parameters.

The methods of Kirkwood and Walker (1986) and Millar(1992) utilize the same underlying statistical model and we will develop this model further here. The other approaches do use statistical tools (e.g. linear or non-linear regression) to varying degrees, but they are used outside of the context of a statistical model appropriate to gillnet catch data. For example, the linear regression approach of Holt (1963) does not model the data as counts and must be applied multiple times because it can only be applied to pairs of gillnets. Hence, the statistical properties of the resulting selectivity estimates are largely unknown. The studies of Helser *et al* (1991,1994) and Henderson and Wong (1991) do not model selectivity but instead follow an historical approach (Hamley,1975) of referring to the catch length distribution as the selection curve.

In this thesis, we shall present a general statistical model that is appropriate for the estimation of gillnet selection curves (i.e. retention probabilities) from comparative gillnet catch data. In many cases, the model is log-linear. Indeed, it was the log-linear reduction that was utilized by Holt(1963) to estimate normal shaped selection curves using catch data from pairs of similar sized mesh gillnets. We make it appropriate to count data from an arbitrary number of mesh sizes and to other shapes of selection curve.

Chapter 3

Terms and Preliminaries

Some selectivity terminology, symbolic notations, definitions and assumptions are introduced in this Chapter. Theoretical background of this work is also provided.

The explanations of the following terms and definitions are taken from published materials and/or industry standard.

Selectivity: the ratio of the number of fish caught by the experimental net to the number of fish exposed to the gear for a given species and size of fish.

Soak Time:the time static gear remains in the water.

Wedging: a fish held tight around the body by a mesh.

Gilling: a fish that enters the net is too large to pass through, and is prevented from retreating by twine that catches the fish behind the gill.

Tangling: a fish that has not necessarily penetrated a mesh is caught in the net by teeth, maxillaries or other projections.

Retention Probability: the probability that a fish, if contacting the gear component, will be retained. It is a function of fish length.

Fishing Effort: The fishing effort is a measure of the amount of fishing, such as the number of hours or days spent fishing, numbers of hooks used (in long line

fishing), kilometers of nets used, etc.

Fishing Power: The fish being caught by a particular gear or vessel from a given density of fish during a certain time interval. Larger vessels have a greater ability to catch more fish and thus have greater fishing power. Also, the improvements in a vessel or gear, such as by adding fish finders, loran, etc., can increase the fishing power.

Capture Range: The smallest fish caught has a maximum girth equal to the perimeter of the mesh; the largest fish caught has a head girth equal to the perimeter of the mesh. Fish between these two sizes are caught.

Selection Range: the difference in length between the fish that has a 75% probability of retention and that with a 25% probability of retention for a certain gear component. Selection range is a measure of sharpness of selection.

Selection Curve: the graphical out-put of the retention probability for the respective length class of fish: the horizontal axis indicates fish length and the vertical axis indicates retention probability for fishes with given length.

The size selection curve for a gillnet is usually a symmetric bell-shaped curve, in which the mode (peak) corresponds to the optimum length and the curve falls away on each side to zero. The explanation is as following: the processes of "wedging" and "gilling" are the most common ways by which a fish becomes meshed in a gillnet. "Wedging" is a function of the maximum girth of a given species and length of fish. "Gilling" is a function of the head girth. The smallest fish caught has a maximum girth equal to the perimeter of the mesh; the largest fish caught has a head girth equal to the perimeter of the mesh. Most fish between these two sizes would be caught. There is an optimum size at which a fish is most likely to be held for sure, being unable to escape. Fish below and above this optimum size, but within the capture range, are less likely to be captured.

The height at a given point on selection curve describes how efficiently the net captures fish with a given size of fish of specific species, while the width and shape of the curve describe the selection range of the gear and the sharpness of its selectivity.

Poisson Process: A Poisson process, named after the French mathematician Simon-Denis Poisson (1781 - 1840), is a stochastic process which is defined in terms of the occurrences of events. This counting process, given as a function of time $N(t)$, Poisson process represents the number of events in the time interval $[0, t]$. Also, the number of events between time a and time b is given as $N(b) - N(a)$.

In probability theory and statistics, the Poisson distribution is a discrete probability distribution that expresses the probability of a number of events occurring in a fixed period of time, if these events occur with a known average rate, and are independent of the time since the last event. The probability that there are exactly k occurrences (k being a non-negative integer, k = 0, 1, 2, ...) is

$$P(k) = f(k, \lambda) = \frac{e^{-\lambda}\lambda^k}{k!} \tag{3.1}$$

where λ is a positive real number, equal to the expected number of occurrences that occur during the given time interval.

Overdispersion: If a count has a Poisson distribution, its variance is equal to its expected value. However, the count data from biological experiments often exhibit excess variances. This is known as overdispersion. It could be induced by grouping behaviour such as the schooling of fish. But general practice indicates that the effect of overdispersion on estimated parameters is negligible and inferential procedures can be suitably amended (McCullagh and Nelder, 1989, p.200)

Likelihood Function: Let X=$(X_1, ..., X_n)$ be a random vector and

$$\{f_X(x \mid \theta),\ \theta \in \Theta\},$$

a statistical model parameterized by $\theta = (\theta_1, ...\theta_k)$, the parameter vector in the parameter space Θ. The likelihood function is a map $L : \Theta \rightarrow \Re$ given by

$$L(\theta \mid x) = f_X(x \mid \theta).$$

In other words, the likelihood function (pdf) is functionally the same form as a probability density function. However, the emphasis is changed from x to θ. The pdf is a function of the x's while holding the parameters θ's constant, while the likelihood is a function of the parameters θ's, while holding the x's constant. When there is no confusion, $L(\theta \mid x)$ is abbreviated to be $L(\theta)$.

The parameter vector $\hat{\theta}$ such that $L(\hat{\theta}) \geq L(\theta)$ for all $\theta \in \Theta$ is called a maximum likelihood estimate, or MLE, of θ.

Maximum Likelihood Estimation: Maximum likelihood estimation begins with writing a mathematical expression known as the Likelihood Function of the sample data. Loosely speaking, the likelihood of a set of data is the probability of obtaining the particular set of data, given the chosen probability distribution model. This expression contains the unknown model parameters. The values of these parameters that maximize the sample likelihood are known as the Maximum Likelihood Estimator or MLE. The general mathematical technique for solving for MLE involves setting partial derivatives of $ln(L)$ (the derivatives are taken with respect to the unknown parameters) equal to zero and solving the resulting equations.

Chapter 4

The Applications of Log-Linear Models

In this chapter, we will use statistical methods to analyze gillnet data.

4.1 Basic Theories

Millar and Holst (1997) present a general statistical log-linear model which is appropriate for the estimation of gillnet selection curves (i.e. retention probabilities) from comparative gillnet catch data. We will use their method to do analysis.

Indeed, it was the log-linear reduction that was utilized by Holt (1963) to estimate normal shaped selection curves catch from pairs of similar sized mesh gillnets. Millar and Holst (1997) refined the method by Holt (1963) and made it appropriate for count data from an arbitrary number of mesh sizes, to other selection curve shapes, and explicitly consider the issue of relative fishing power of the meshes. They fitted several such models to gillnet catch data of Fraser River sockeye salmon (Holt, 1963). The following are the details of their method.

For gillnets and hooks, a fish may make multiple contact with the gear if it is not caught on the first occasion. Therefore, in using the method presented here, one must be willing to accept that, with regard to the statistical distribution of the catch frequencies, multiple contact of a single fish is adequately modeled as single contact by multiple fish (Millar, 1992).

The number $y_{l,j}$, standing for the fish with a length of l that encounter the jth gillnet are assumed to be Poisson Process with parameter λ_l based on the following:

a)the probability of a length l_i fish coming in contact with the gear in any short time interval $[t,t+\triangle t]$ is approximately $\lambda_l \triangle t$, which is approximately proportional to the length of the interval for all values of t;

b)the probability of more than one length l_i fish coming in contact with the gear in interval $[t,t+\triangle t]$ is almost 0, when $\triangle t \rightarrow 0$;

c)the number of length l_i fish coming in contact with the gear in any interval of time is independent of the number of length l_i fish coming in contact with the gear in any other non-overlapping interval of time.

So $y_{l,j}$ is identified as Poisson Process

$$y_{lj} \sim P(p_j \lambda_l), \tag{4.1}$$

where the expected count, $p_j \lambda_l$, is the product of the abundance of fish with length class l (λ_l), and the relative fishing intensity of gillnet j (p_j).

Let $r_j(l)$ denote the retention probability of fish with length l in the jth gear. It then easily follows that the number n_{lj}, standing for the observed number of the length l fish caught in the jth net, can be described as observations from independent Poisson distributions $N_{l,j}$

$$N_{lj} \sim P(p_j \lambda_l r_l(j)) \tag{4.2}$$

Likewise it is natural to model the abundance over length classes as a continuous function, rather than by using discrete parameters for the individual length classes. For a valid and useful application of the extended model, which includes fitting of a continuous population, it is necessary to collect information on the structure of abundance in order to enable a reasonable choice of the functional form. This is often not the case. And hence the simple analysis, aimed only at fitting the selection curves, will probably be the most common practise. No precise guidelines can be given on this topic, but if reliable information can be collected, either from direct experiments,previous studies,biological knowledge or in other ways, the (pre-)analysis should include an estimation of the abundance λ_l. The same concerns also apply for modeling the intensity parameter. An example of a useful application of such is in the case where not all the nets are with the same length. Under that situation, the efficiency of the jth net can be suitably modeled to be proportional to the length of that net

$$p_j = cl_j \tag{4.3}$$

where l_j is the length of the jth net and c is a constant. The likelihood function is

$$\prod_{l,j} \frac{(p_j \lambda_l r_j(l))^{n_{lj}}}{(n_{lj})!} e^{-v_{lj}} \tag{4.4}$$

where $v_{lj} = p_j \lambda_l r_l(j)$. Hence, the log likelihood function becomes

$$L = \sum_{l,j} n_{lj} log(v_{lj}) - v_{lj} = \sum_{l,j} n_{lj}[log(p_j) + log(\lambda_l) + log(r_j(l))] - p_j \lambda_l r_j(l) \tag{4.5}$$

where the term$-log(n_{lj}!)$ has been omitted.

However, for a large range of choice for the components p_j, λ_l, and $r_j(l)$, it is likely to get

$$log(v_{lj}) = log(p_j) + log(\lambda_l) + log(r_j(l)) = \sum_i a_i f_i(l,j) \tag{4.6}$$

where $f_i(l,j)$ are functions depending only on mesh-size and/or length-classes. The advantage of using this transcription is that it greatly facilitates the estimation.

4.1.1 Normal Location

If the selection curves($r_j(l)$) are assumed to be normal location,

$$r_j(l) = exp\left(-\frac{(l - k * m_j)^2}{2\sigma^2}\right),$$

we can get

$$\begin{aligned} log(v_{lj}) &= log(p_j) + log(\lambda_l) + log(r_j(l)) \\ &= log(p_j) + log(\lambda_l) - \frac{(l - km_j)^2}{2\sigma^2} \\ &= log(p_j) + log(\lambda_l) - \frac{l^2 - 2lkm_j + k^2m_j^2}{2\sigma^2} \\ &= log(p_j) + log(\lambda_l) - \frac{l^2}{2\sigma^2} + \frac{klm_j}{\sigma^2} - \frac{k^2m_j^2}{2\sigma^2} \\ &= log(p_j) + log(\lambda_l) + \alpha_0 + \alpha_1 lm_j + \alpha_2 m_j^2 \end{aligned}$$

where $\alpha_0 = -\frac{l^2}{2\sigma^2}$, $\alpha_1 = \frac{k}{\sigma^2}$, $\alpha_2 = \frac{k^2}{2\sigma^2}$.

4.1.2 Normal Scale

If the selection curves are assumed to be normal scale, then we get

$$r_j(l) = exp\left(-\frac{(l - k_1 * m_j)^2}{2k_2 * m_j^2}\right)$$

If geometric similarity is assumed, the spread of jth gillnet σ_j is proportional to the mesh size,m_j. A convenient parametrization is μ_j=$k_1 m_j$ and σ_j^2=$k_2 m_j^2$, here k_1 and k_2 are to be estimated. Then,

$$\begin{aligned} log(v_{lj}) &= log(p_j) + log(\lambda_l) + log(r_j(l)) \\ &= log(p_j) + log(\lambda_l) - \frac{(l-\mu_j)^2}{2\sigma_j^2} \\ &= log(p_j) + log(\lambda_l) - \frac{(l-k_1 m_j)^2}{2k_2 m_j^2} \\ &= log(p_j) + log(\lambda_l) - \frac{k_1^2}{2k_2} + \frac{k_1}{k_2}\frac{l}{m_j} - \frac{1}{2k_2}(\frac{l}{m_j})^2 \\ &= log(p_j) + log(\lambda_l) + \alpha_0 + \alpha_1 \frac{l}{m_j} + \alpha_2 (\frac{l}{m_j})^2 \end{aligned}$$

where α_0=$-\frac{k_1^2}{2k_2}$, α_1=$-\frac{k_1}{k_2}$, α_2=$-\frac{1}{2k_2}$.

4.1.3 Gamma

If the selection curves are assumed to be gamma, then we get

$$r_j(l) = (\frac{l}{(\alpha-1)*k*m_j})^{\alpha-1} * exp(\alpha - 1 - \frac{l}{k*m_j})$$

so we can get

$$\begin{aligned} log(v_{lj}) &= log(p_j) + log(\lambda_l) + log(r_j(l)) \\ &= log(p_j) + log(\lambda_l) + (\alpha-1)log(\frac{l}{(\alpha-1)*k*m_j}) + (\alpha - 1 - \frac{l}{k*m_j}) \\ &= log(p_j) + log(\lambda_l) + (\alpha-1)log(\frac{1}{(\alpha-1)*k} * \frac{l}{m_j}) + (\alpha - 1 - \frac{l}{k*m_j}) \\ &= log(p_j) + log(\lambda_l) + (\alpha-1)log(\frac{1}{(\alpha-1)*k}) + \alpha - 1 + (\alpha-1)log(\frac{l}{m_j}) - \frac{l}{k*m_j} \\ &= log(p_j) + log(\lambda_l) + (\alpha-1)log(\frac{1}{(\alpha-1)*k}) + \alpha - 1 + (\alpha-1)log(\frac{l}{m_j}) - \frac{1}{k} * \frac{l}{m_j} \\ &= log(p_j) + log(\lambda_l) + \alpha_0 + \alpha_1 log(\frac{l}{m_j}) + \alpha_2(\frac{l}{m_j}) \end{aligned}$$

where α_0=$(\alpha-1)log(\frac{1}{(\alpha-1)*k}) + \alpha - 1$, α_1=$\alpha - 1$, α_2=$\frac{1}{k}$.

4.1.4 Lognormal

If the selection curves are assumed to be lognormal, then we get

$$r_j(l) = \frac{1}{l} exp(\mu_1 + log(\frac{m_j}{m_1}) - \frac{\sigma^2}{2} - \frac{(log(l) - \mu_1 - log(\frac{m_j}{m_1}))^2}{2\sigma^2})$$

so we can get

$$\begin{aligned}
log(v_{lj}) &= log(p_j) + log(\lambda_l) + log(r_j(l)) \\
&= log(p_j) + log(\lambda_l) + \mu_1 + log(\frac{m_j}{m_1}) - \frac{\sigma^2}{2} - \frac{(log(l) - \mu_1 - log(\frac{m_j}{m_1}))^2}{2\sigma^2} - log(l) \\
&= log(p_j) + log(\lambda_l) + \mu_1 - \frac{\sigma^2}{2} - log(l) + log(\frac{m_j}{m_1}) - \frac{(log(l) - \mu_1 - log(\frac{m_j}{m_1}))^2}{2\sigma^2} \\
&= log(p_j) + log(\lambda_l) + \mu_1 - \frac{\sigma^2}{2} - log(l) + log(\frac{m_j}{m_1}) \\
&\quad - \frac{((log(l) - \mu_1)^2 - 2(log(l) - \mu_1)log(\frac{m_j}{m_1}) + log(\frac{m_j}{m_1})^2}{2\sigma^2} \\
&= log(p_j) + log(\lambda_l) + \mu_1 - \frac{\sigma^2}{2} - log(l) + log(\frac{m_j}{m_1}) - \frac{\mu_1}{\sigma^2} log(\frac{m_j}{m_1}) \\
&\quad - \frac{((log(l) - \mu_1)^2 - 2log(l)log(\frac{m_j}{m_1}) + log(\frac{m_j}{m_1})^2}{2\sigma^2} \\
&= log(p_j) + log(\lambda_l) + \mu_1 - \frac{\sigma^2}{2} - log(l) + \frac{(log(l) - \mu_1)^2}{2\sigma^2} + log(\frac{m_j}{m_1}) - \frac{\mu_1}{\sigma^2} log(\frac{m_j}{m_1}) \\
&\quad - \frac{-2log(l)log(\frac{m_j}{m_1}) + log(\frac{m_j}{m_1})^2}{2\sigma^2} \\
&= log(p_j) + log(\lambda_l) + \mu_1 - \frac{\sigma^2}{2} - log(l) + \frac{(log(l) - \mu_1)^2}{2\sigma^2} \\
&\quad + \frac{1}{\sigma^2}(log(l)log(\frac{m_j}{m_1}) - \frac{1}{2}log(\frac{m_j}{m_1})^2) + (1 - \frac{\mu_1}{\sigma^2})log(\frac{m_j}{m_1}) \\
&= log(p_j) + log(\lambda_l) + \alpha_0 + \alpha_1(log(l)log(\frac{m_j}{m_1}) - \frac{1}{2}log(\frac{m_j}{m_1})^2) + \alpha_2 log(\frac{m_j}{m_1})
\end{aligned}$$

where $\alpha_0 = \mu_1 - \frac{\sigma^2}{2} - log(l) + \frac{(log(l)-\mu_1)^2}{2\sigma^2}$, $\alpha_1 = \frac{1}{\sigma^2}$, $\alpha_2 = (1 - \frac{\mu_1}{\sigma^2})$.

From the above, we can get the following four models that we shall use in this thesis.

Model	Selection Curve $r_j(l)$	$\sum_i [\alpha_i] * f_i(l,j)$
Normal Location	$exp(-\frac{(l-k*m_j)^2}{2\sigma^2})$	$[\frac{k}{\sigma^2}] * \{l * m_j\} + [-\frac{k^2}{2\sigma^2}] * \{m_j^2\}$
Normal Scale	$exp(-\frac{(l-k_1*m_j)^2}{2k_2*m_j^2})$	$[\frac{k_1}{k_2}] * \{\frac{l}{m_j}\} + [-\frac{1}{2k_2}] * (\frac{l}{m_j})^2$
Gamma	$(\frac{l}{(\alpha-1)*k*m_j})^{\alpha-1} * exp(\alpha - 1 - \frac{l}{k*m_j})$	$[\alpha - 1] * \{log(\frac{l}{m_j})\} + [-\frac{1}{k}] * \{\frac{l}{m_j}\}$
Lognormal	$\frac{1}{l} exp(\mu_1 + log(\frac{m_j}{m_1}) - \frac{\sigma^2}{2} - \frac{(log(l)-\mu_1-log(\frac{m_j}{m_1}))^2}{2\sigma^2})$	$[\frac{1}{\sigma^2}] * \{log(l) * log(\frac{m_j}{m_1}) - \frac{1}{2}log^2(\frac{m_j}{m_1})\} + [1 - \frac{\mu_1}{\sigma^2}] * \{log(\frac{m_j}{m_1})\}$

Table 4.1: Results for Fleet EW, the degrees of freedom is 180

4.2 Results and Conclusion

In this section, we will discuss the results by Millar and Holst (1997) and our results.

4.2.1 Results By Millar and Holst (1997)

	Equal fishing power		Fishing power α mesh-size	
Model	Deviance	$\frac{D}{df}$	Deviance	$\frac{D}{df}$
Normal Location	862.9	11.505	883.6	11.781
Normal Scale	772.8	10.304	773.2	10.309
Gamma	719.3	9.591	719.3	9.591
Log normal	704.3	9.391	704.3	9.391

Table 4.2: Results By Millar and Holst (1997), the degrees of freedom is 75

Millar and Holst (1997) fitted each selection curve twice, first under the assumption of equal fishing power of the gillnets and then again assuming fishing power to be proportional to mesh size (Table 4.2). In our analysis, we will only fit the selection curve under the assumption of equal fishing power.

They used deviance (D) as a tool to measure the overall goodness of fit. Overall, the lognormal selection curve provided the best fit. However, the model deviance(D) is 704.30 on 75 d.f. indicates overdispersion and/or severe lack of fit.

4.2.2 Our Results

By using the above methods, we can get the following results.

The original data and splus source code can be found in appendix.

	Mesh 1		Mesh 2		Mesh 3	
Model	Parameters	Deviance	Parameters	Deviance	Parameters	Deviance
Normal Location	(μ,σ)=(68.56,12.08)	421.86	(μ,σ)=(74.79,12.08)	421.86	(μ,σ)=(81.02,12.08)	421.86
Normal Scale	(μ,σ)=(69.74,19.70)	427.11	(μ,σ)=(76.08,21.49)	427.11	(μ,σ)=(82.42,23.28)	427.11
Gamma	(α,β)=(38.95,1.81)	422.07	(α,β)=(38.95,1.98)	422.07	(α,β)=(38.95,2.14)	422.07
Log normal	(μ,σ)=(4.26,0.17)	431.74	(μ,σ)=(4.34,0.17)	431.74	(μ,σ)=(4.42,0.17)	431.74

Table 4.3: Results for Fleet EW, the degrees of freedom is 180

	Mesh 1		Mesh 2		Mesh 3	
Model	Parameters	Deviance	Parameters	Deviance	Parameters	Deviance
Normal Location	(μ,σ)=(69.72,10.97)	667.20	(μ,σ)=(76.06,10.97)	667.20	(μ,σ)=(82.40,10.97)	667.20
Normal Scale	(μ,σ)=(68.38,12.46)	617.86	(μ,σ)=(74.59,13.59)	617.86	(μ,σ)=(80.81,14.73)	617.86
Gamma	(α,β)=(47.78,1.50)	669.16	(α,β)=(47.78,1.63)	669.16	(α,β)=(47.78,1.77)	669.16
Log normal	(μ,σ)=(4.31,0.17)	705.20	(μ,σ)=(4.39,0.17)	705.20	(μ,σ)=(4.47,0.17)	705.20

Table 4.4: Results for Fleet JV, the degrees of freedom is 180

The result of deviance (D) and $\frac{D}{df}$ (Manual for Gillnet Selectivity, 1996) are shown in table 4.3 and 4.4.

	EW		JV	
Model	Deviance	$\frac{D}{df}$	Deviance	$\frac{D}{df}$
Normal Location	421.86	2.344	667.20	3.701
Normal Scale	427.11	2.373	617.86	3.433
Gamma	422.07	2.345	669.16	3.718
Log normal	431.74	2.399	705.20	3.918

Table 4.5: Deviance for EW and JV

$\frac{D}{df}$ can be used to check if the data is overdispersed or lack of fit (Millar and Hoslt, 1997). We can find the $\frac{D}{df}$ of our results are much less than their of Millar and Holst (1997), which means the method of Millar and Hoslt can be used to fit our turbot data. There maybe are several reasons for that. Firstly, sockeye and turbot are different fish. Their girth and headgirth are different. So the fishing process are different. Secondly, the data of Holt (1963) have 8 different mesh sizes and 11 different fish lengths. However, our data have 3 different mesh sizes and 91 different fish lengths.

We will analysis the result of each model.

Normal Location Model

Firstly, we can get plots of fitted catch for Normal Location Model.

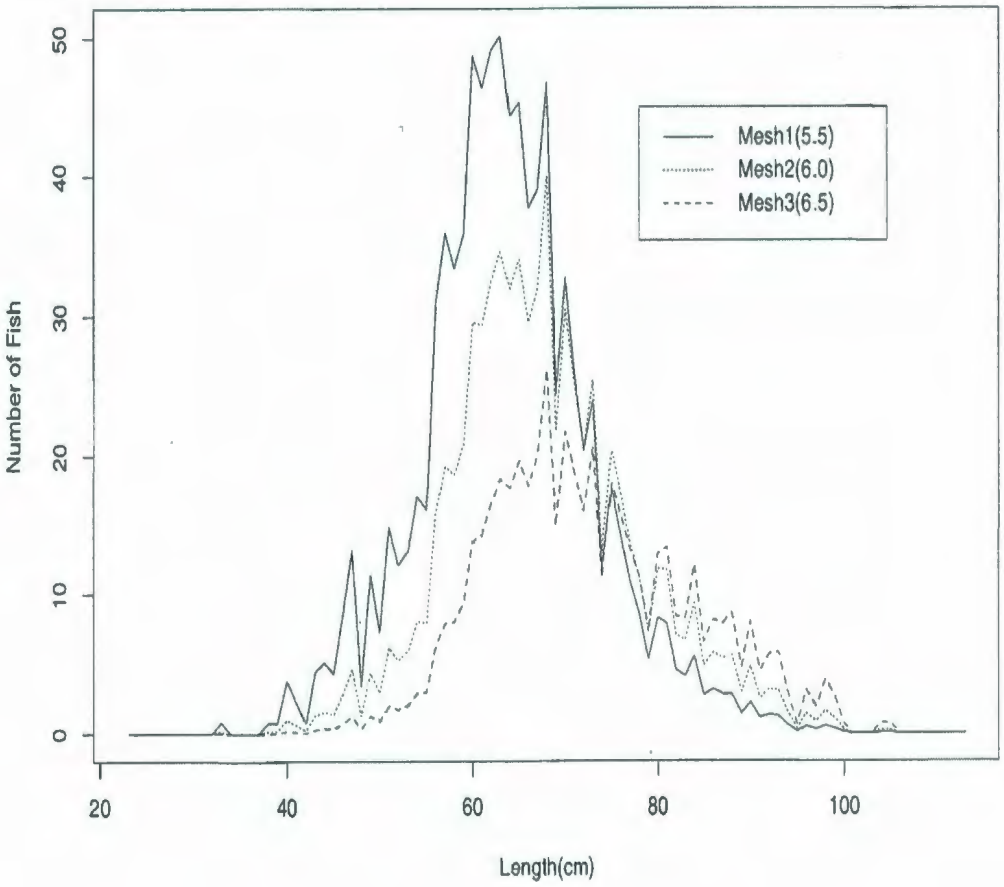

Figure 4.1: EW Normal Location Fitted Catch

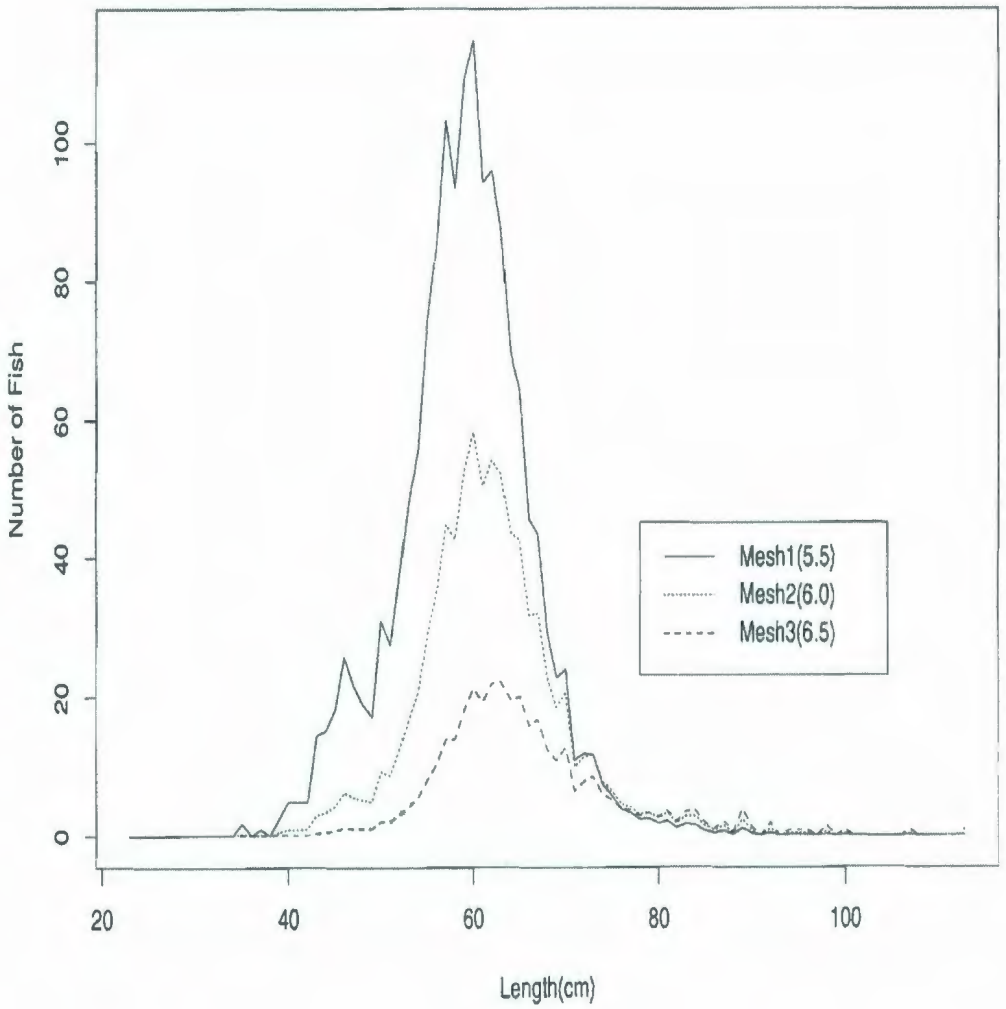

Figure 4.2: JV Normal Location Fitted Catch

Secondly, we can get deviance residuals plots (McCullangh and Nelder, 1989) for Normal Location Model. If $\frac{D}{df}$ are greater than 1, the deviance residuals plots can be used to check if the data is overdispersed or lack of fit.

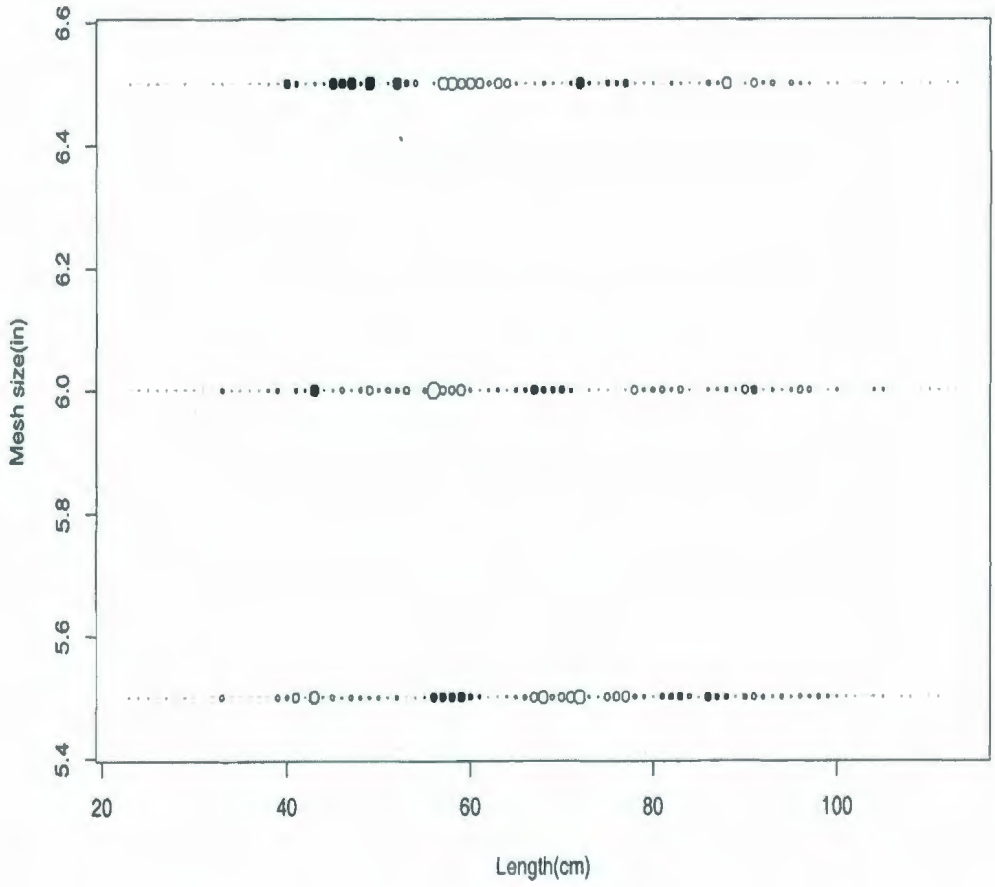

Figure 4.3: Deviance Residuals of Normal Location for EW

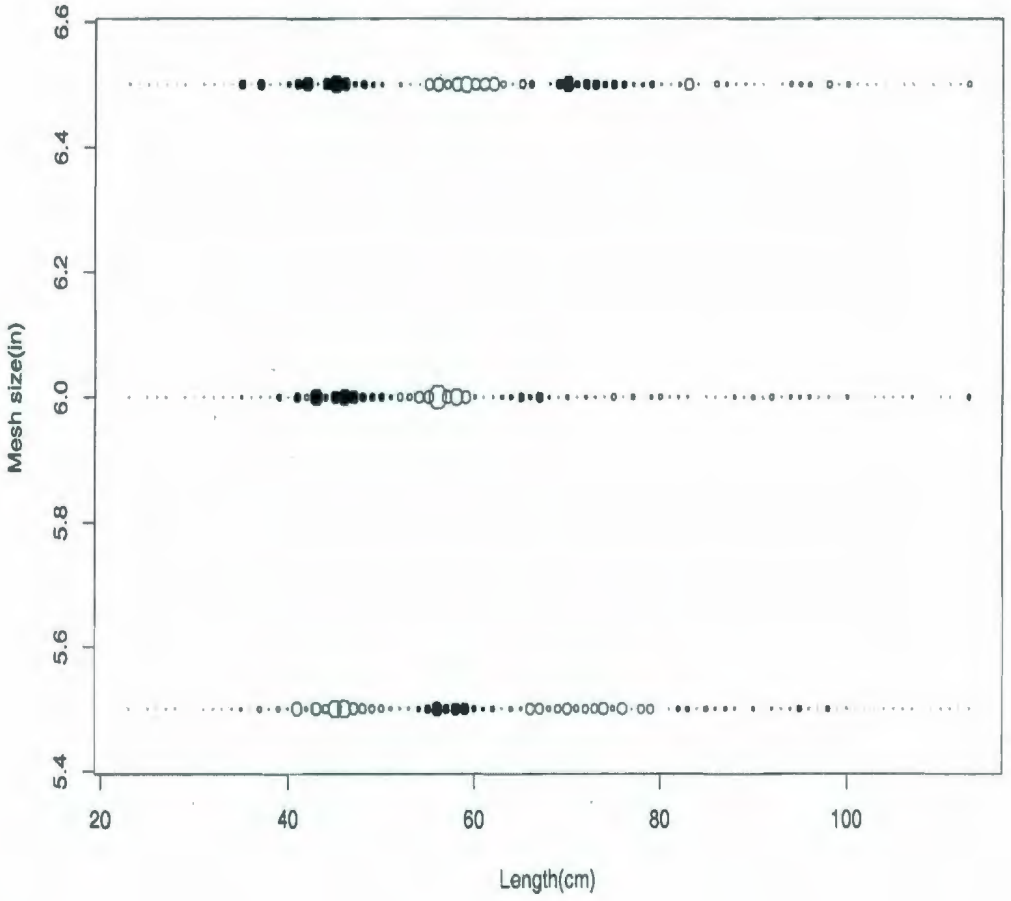

Figure 4.4: Deviance Residuals of Normal Location for JV

From the above deviance residuals plots (McCullangh and Nelder, 1989), we can find there is indeed lack of fit.

Finally, we can plot the selection curve, which is a convenient presentation of the overall fit. Plot of selection curve gives a quick and qualitative impression of the fit, that is an intuitive assessment of its plausibility. And plots of selection curve are more of visual interest rather than an actual quantitative justification.

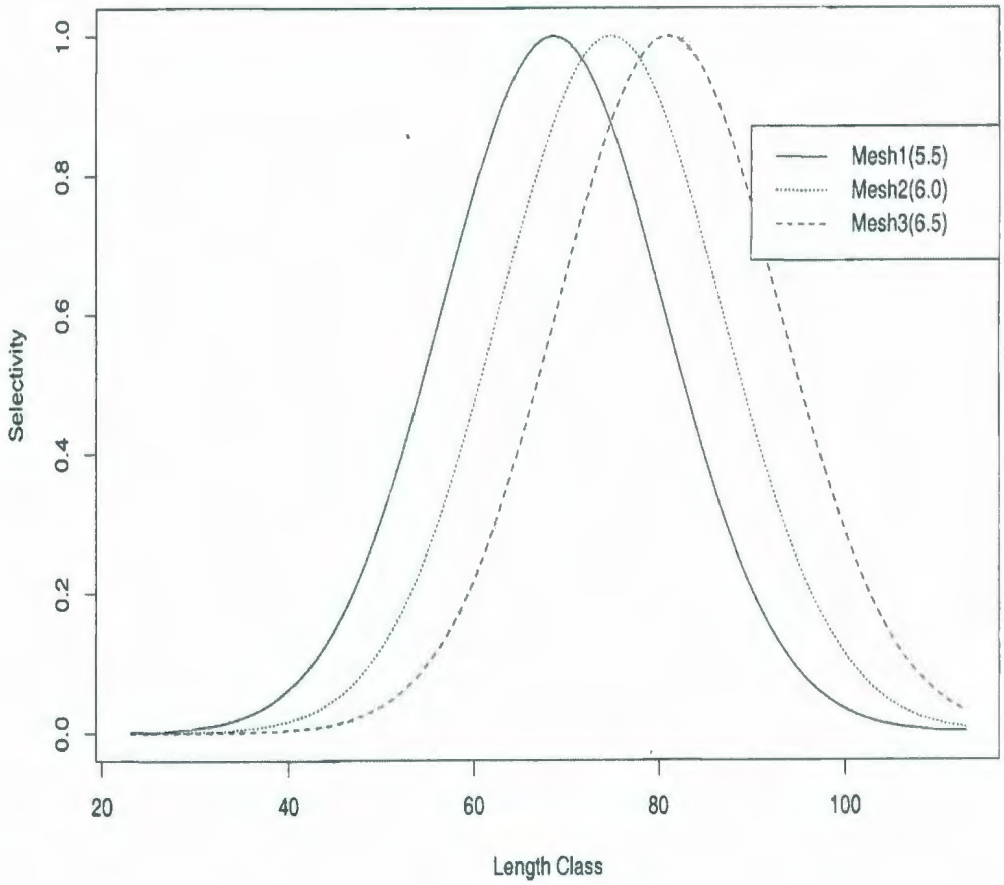

Figure 4.5: EW Normal Location Selection Curves

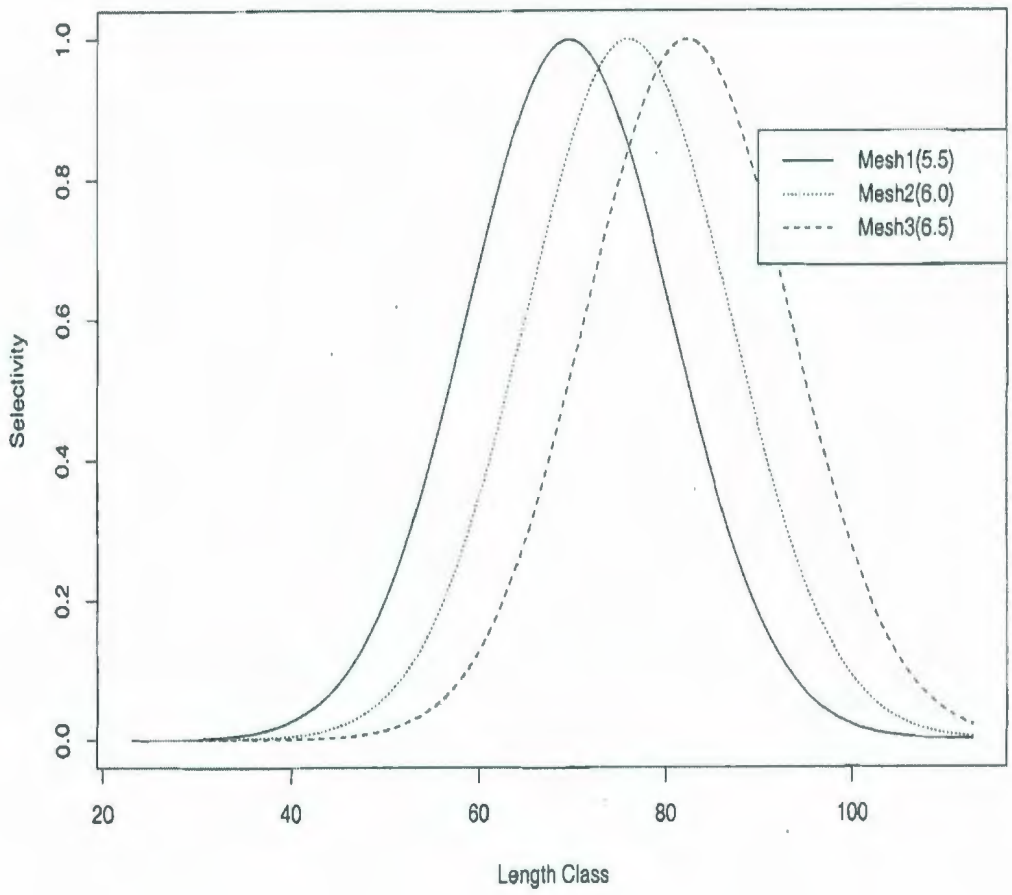

Figure 4.6: JV Normal Location Selection Curves

Normal Scale Model

Firstly, we can get plots of fitted catch for Normal Scale Model.

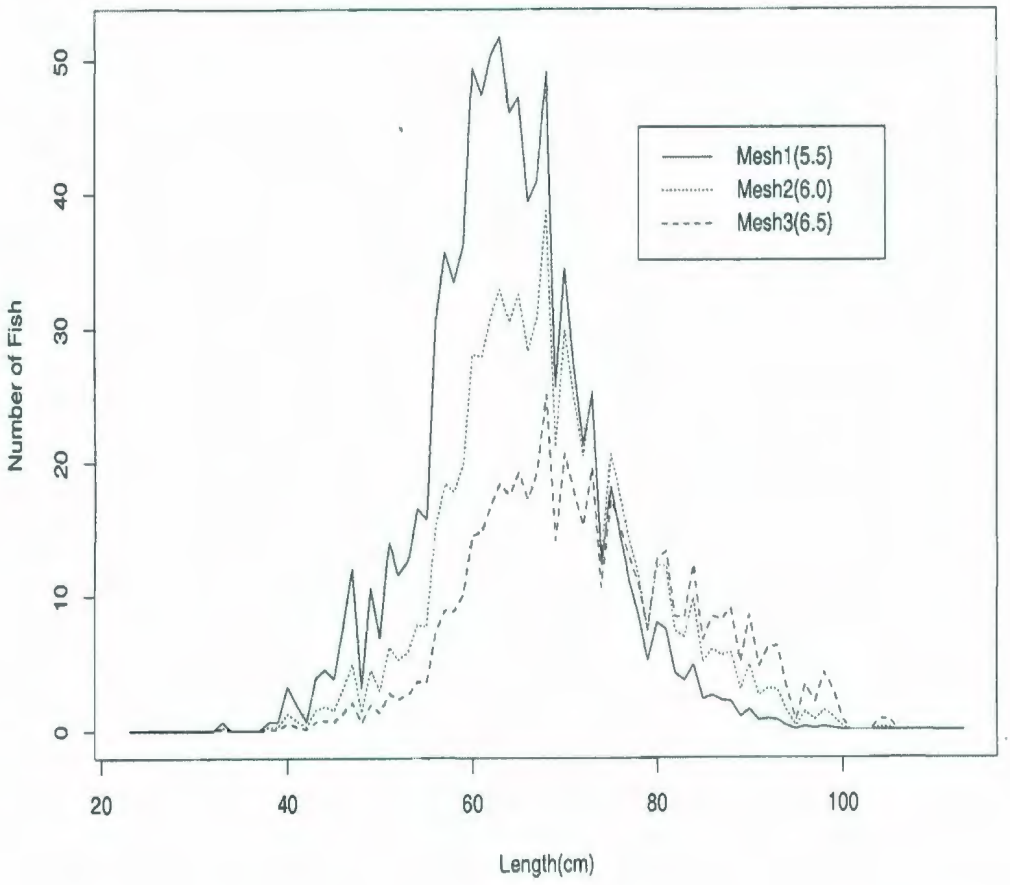

Figure 4.7: EW Normal Scale Fitted Catch

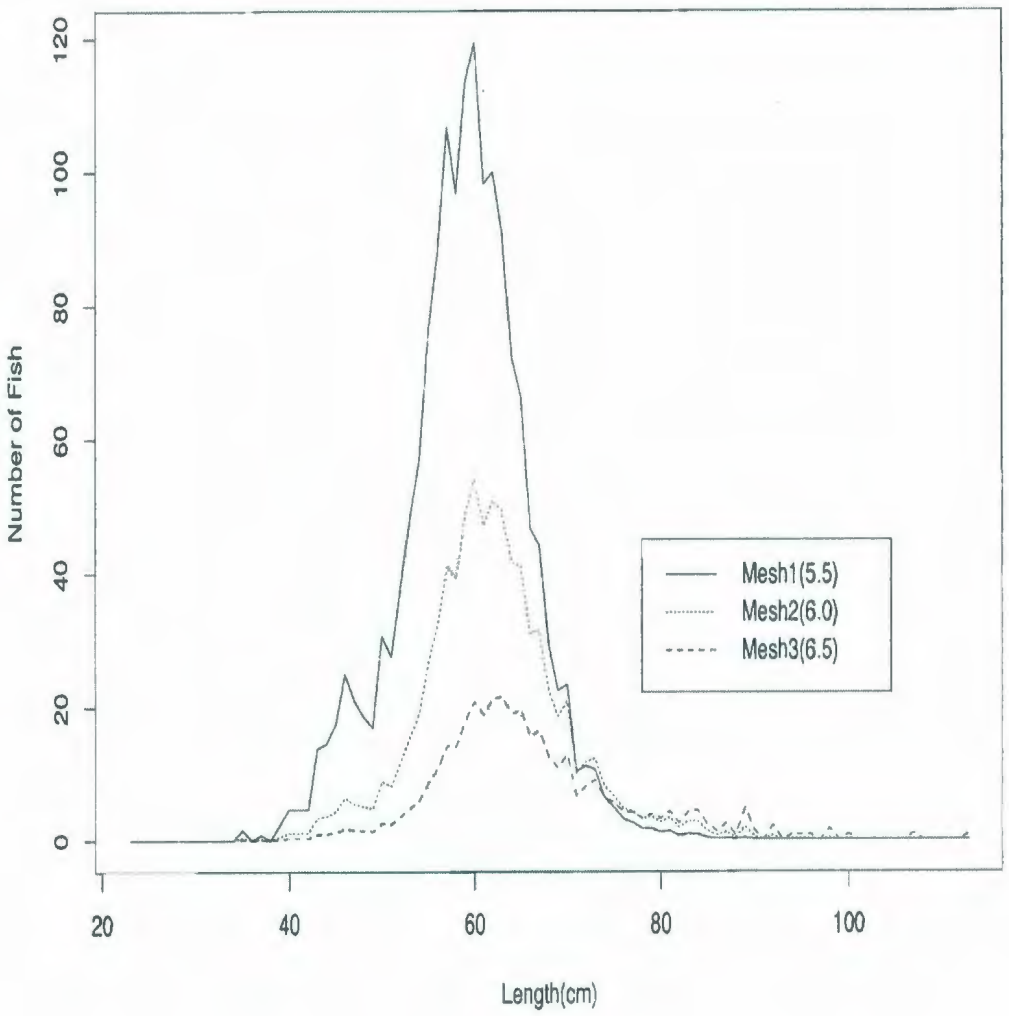

Figure 4.8: JV Normal Scale Fitted Catch

Secondly, we can get deviance residuals plots (McCullangh and Nelder, 1989) for Normal Location Model. If $\frac{D}{df}$ are greater than 1, the deviance residuals plots can be used to check if the data is overdispersed or lack of fit.

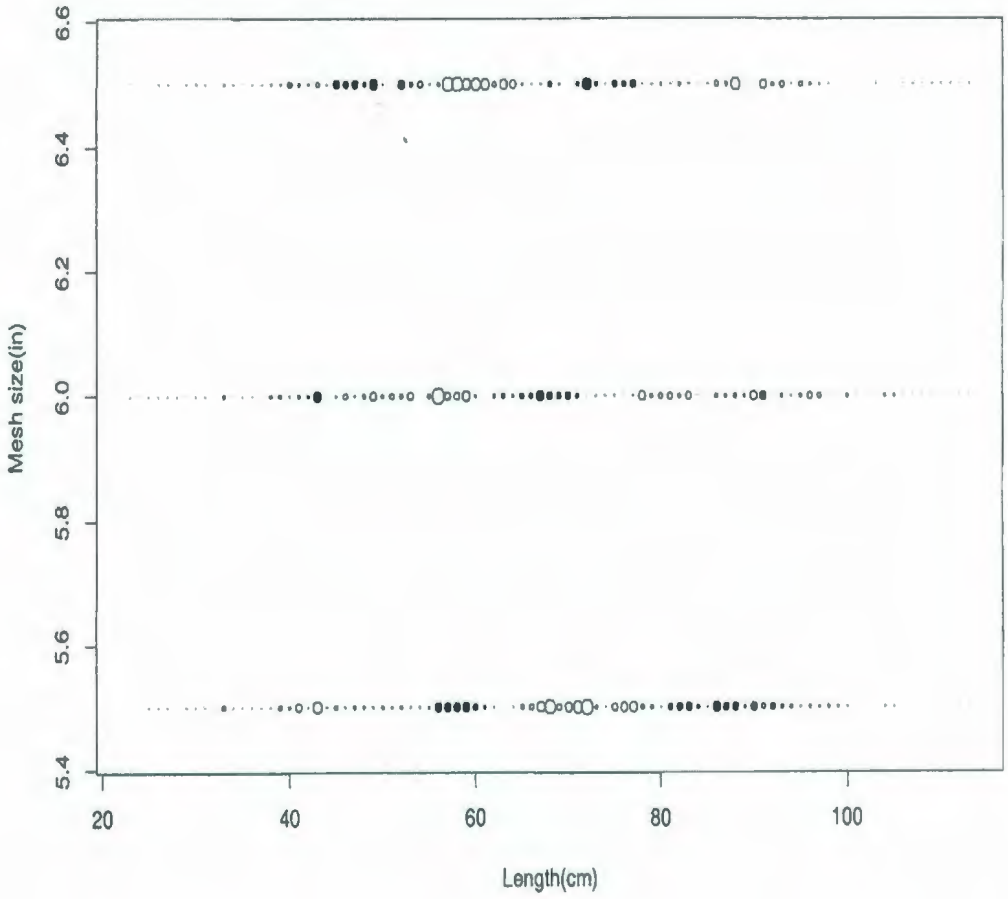

Figure 4.9: Deviance Residuals of Normal Scale for EW

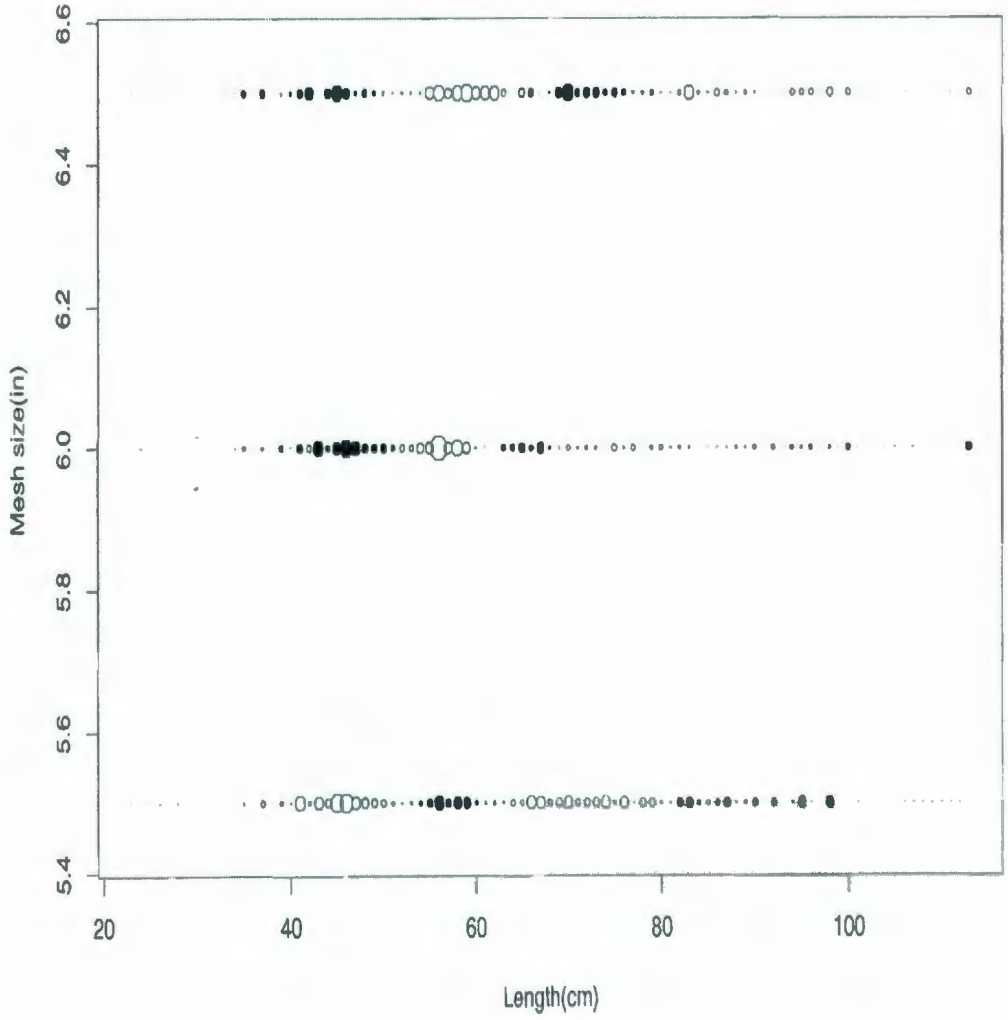

Figure 4.10: Deviance Residuals of Normal Scale for JV

From the above deviance residuals plots (McCullangh and Nelder, 1989), we can find there is indeed lack of fit.

Finally, we can get plot of selection curve, which is a convenient presentation of the overall fit. Plot of selection curve gives a quick and qualitative impression of the fit, that is an intuitive assessment of its plausibility. And plots of selection curve are more of visual interest rather than an actual quantitative justification.

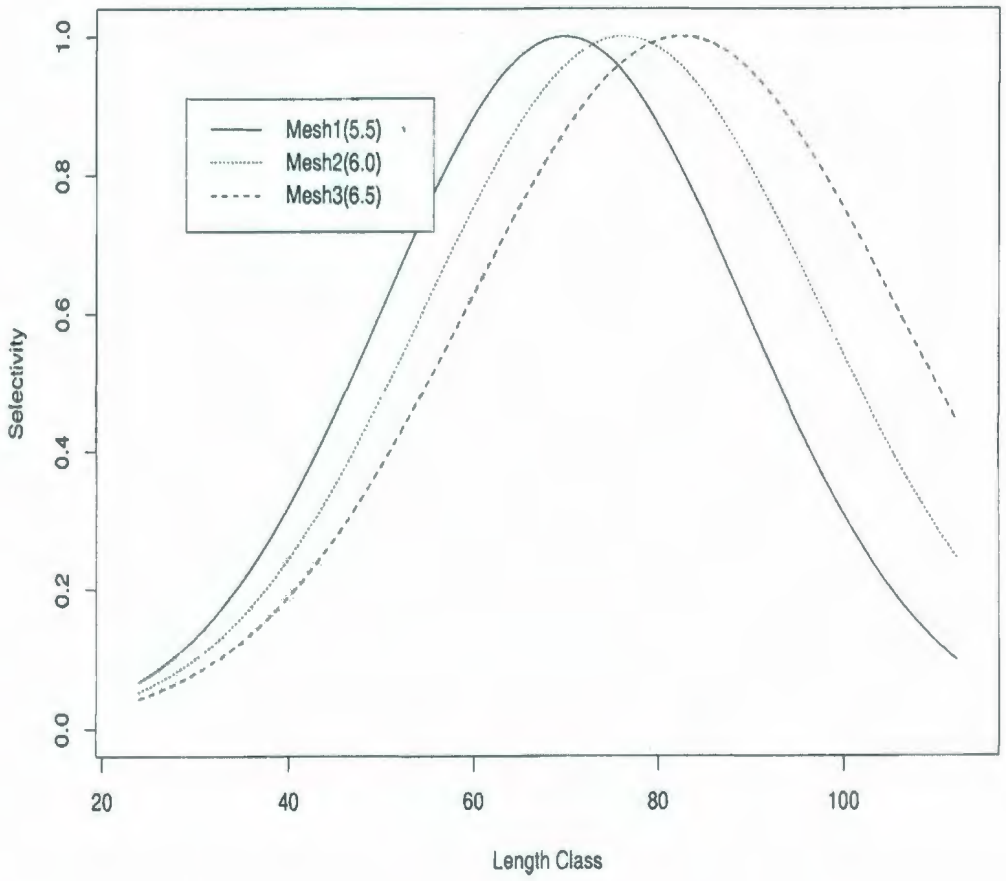

Figure 4.11: EW Normal Scale Selection Curves

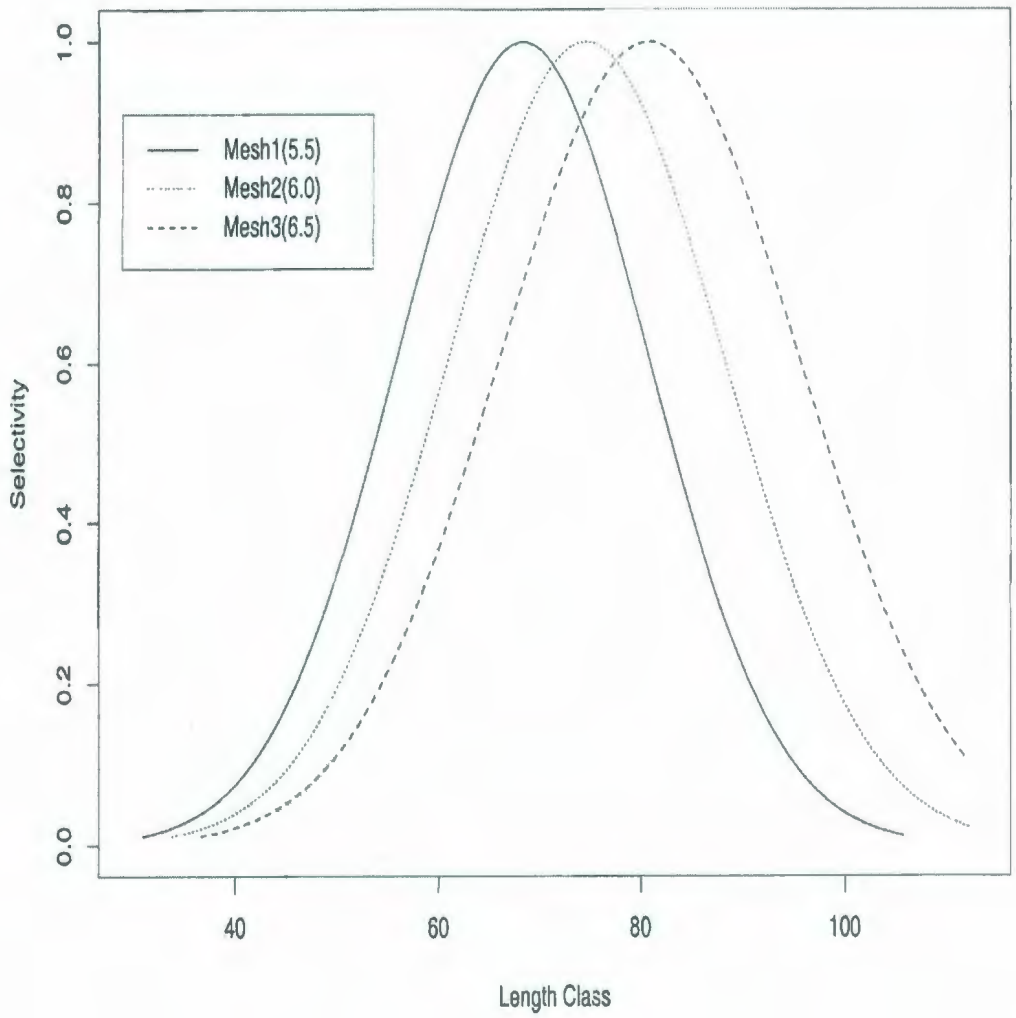

Figure 4.12: JV Normal Scale Selection Curves

Lognormal Model

Firstly, we can get plots of fitted catch for Lognormal Model.

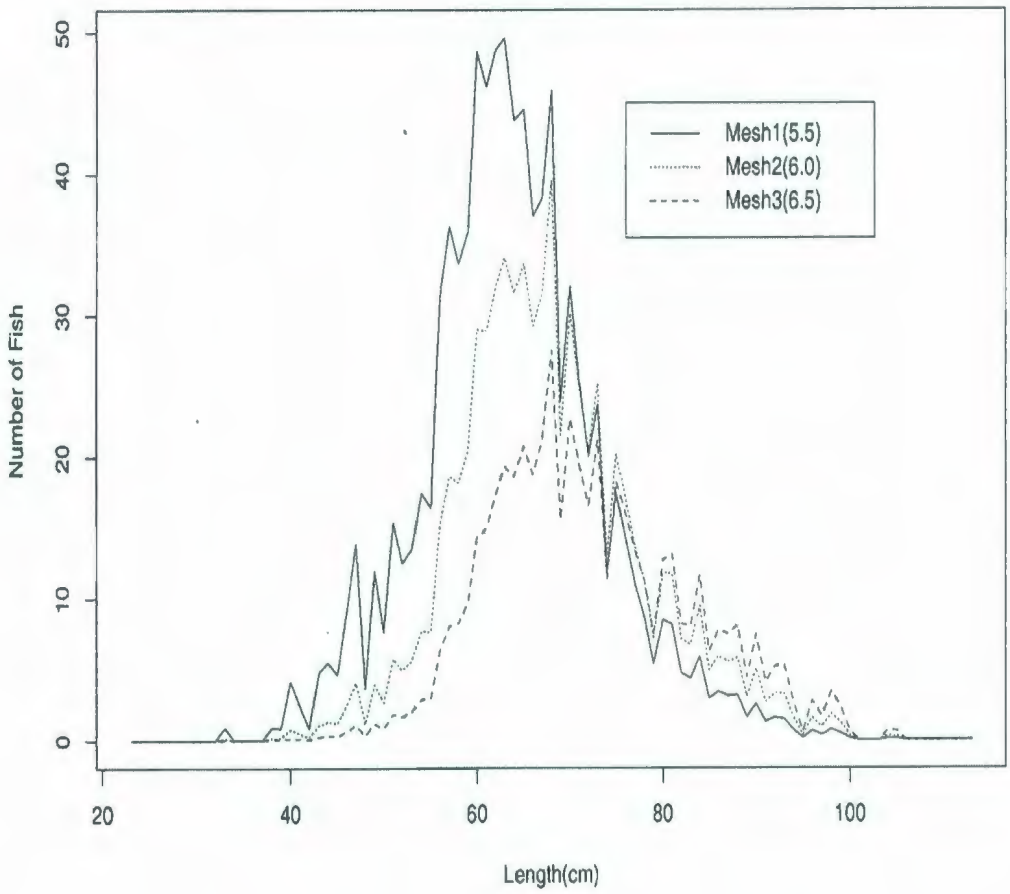

Figure 4.13: EW Lognormal (mesh 1) Fitted Catch

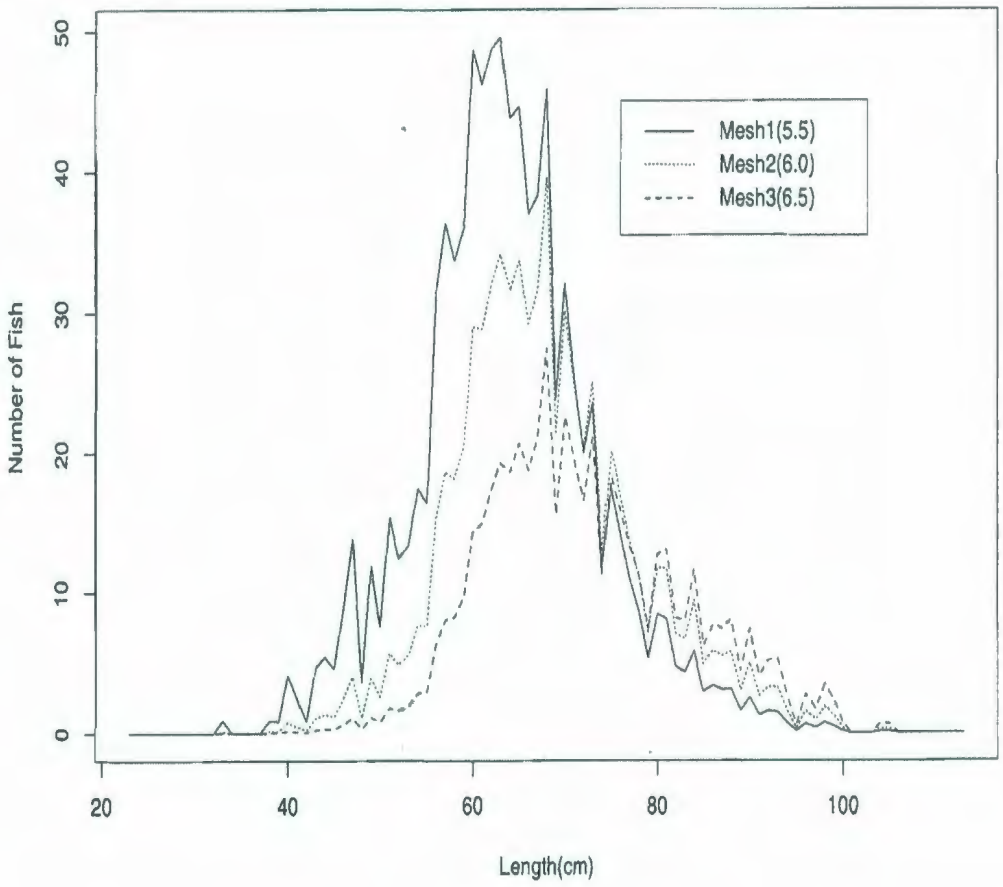

Figure 4.14: EW Lognormal (mesh 2) Fitted Catch

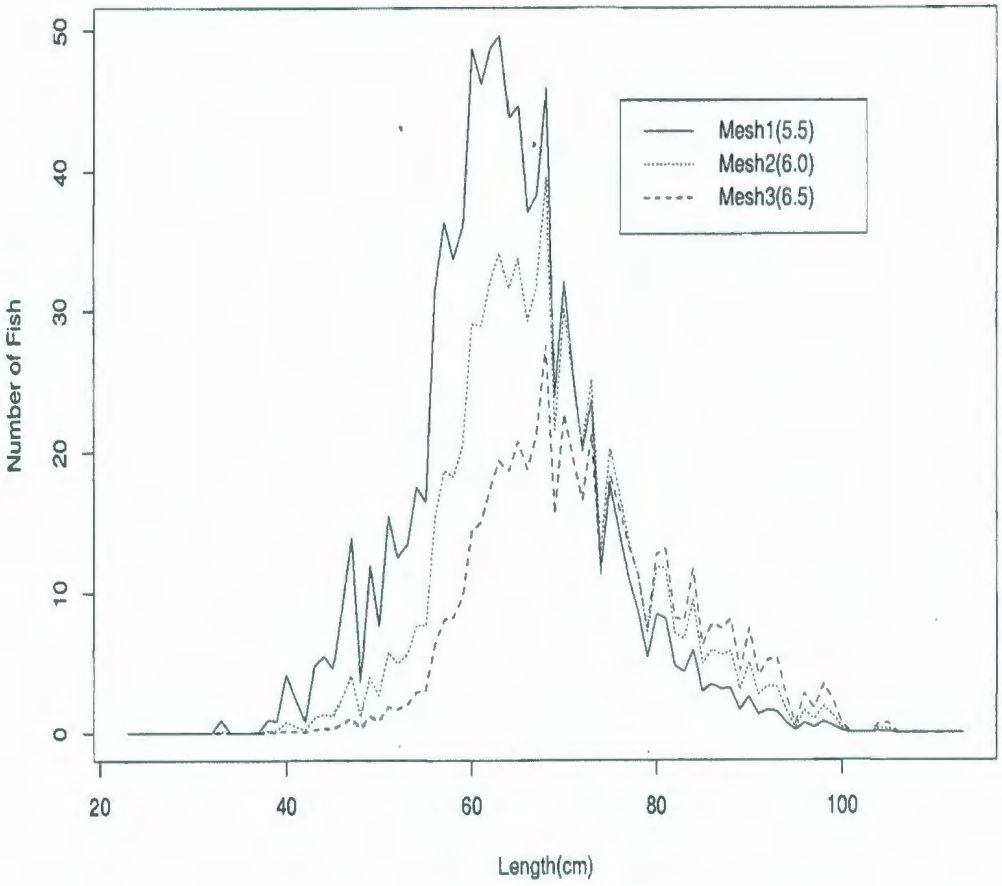

Figure 4.15: EW Lognormal (mesh 3) Fitted Catch

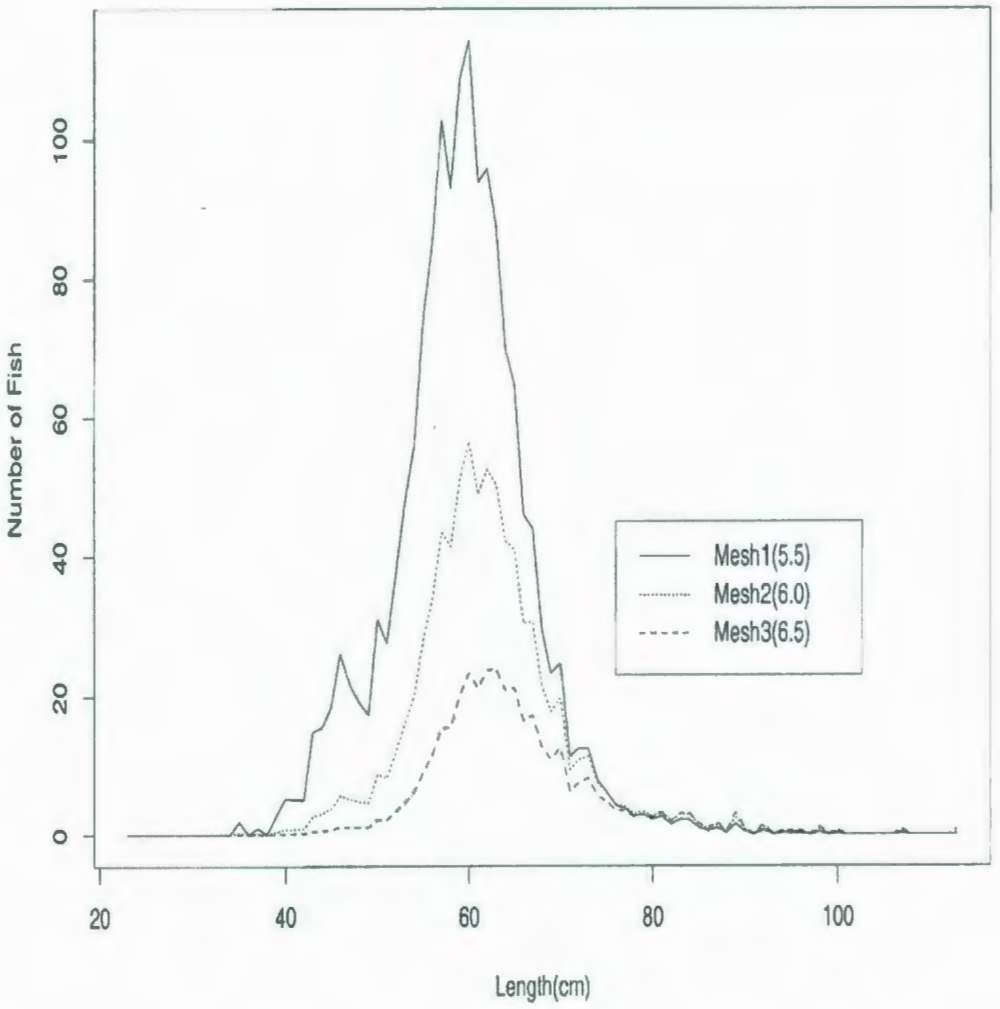

Figure 4.16: JV Lognormal (mesh 1) Fitted Catch

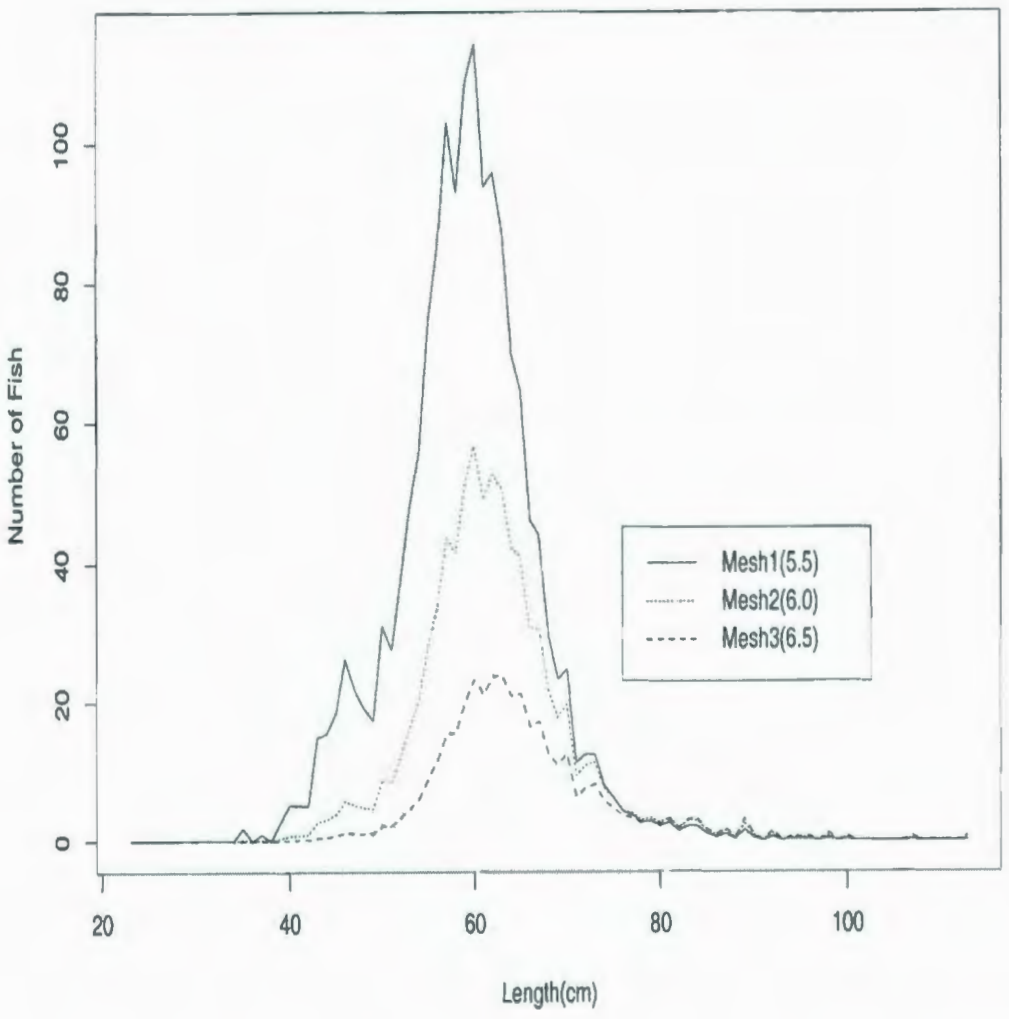

Figure 4.17: JV Lognormal (mesh 2) Fitted Catch

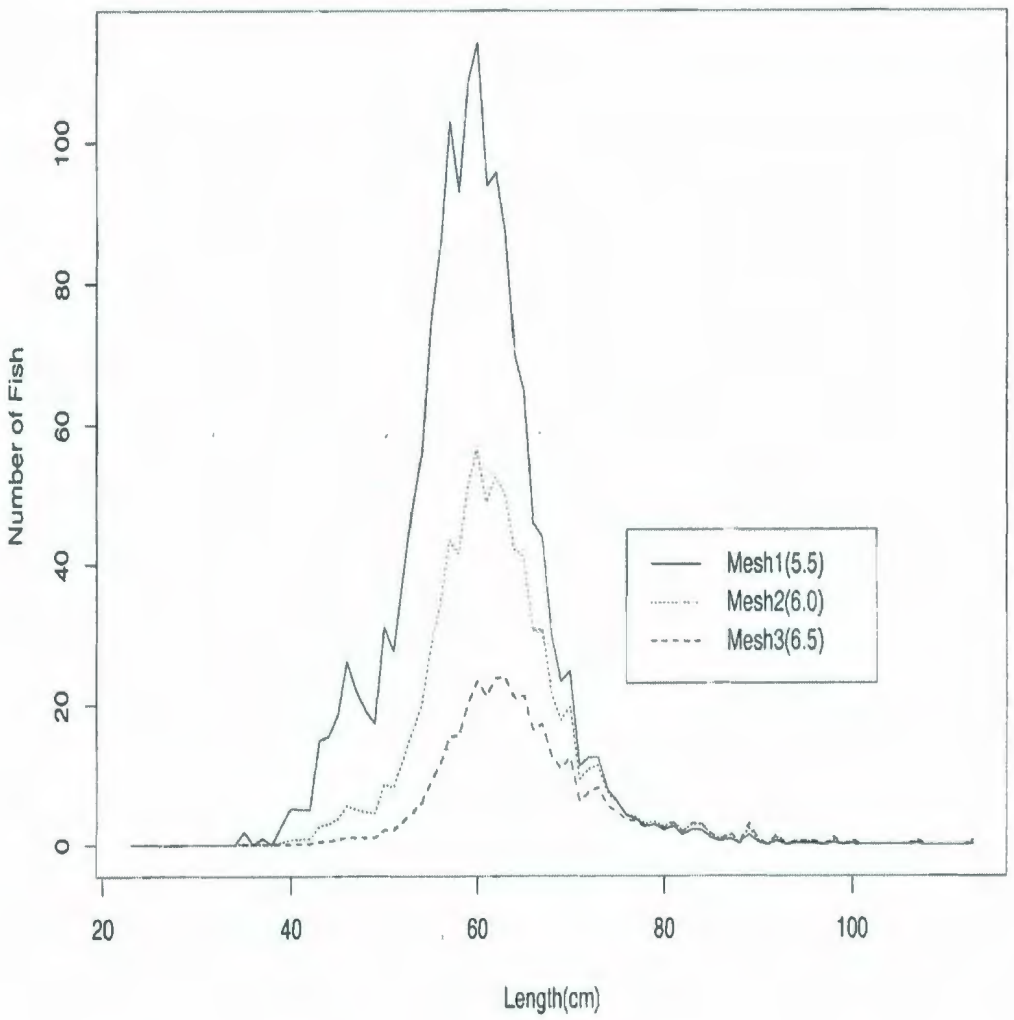

Figure 4.18: JV Lognormal (mesh 3) Fitted Catch

Secondly, we can get deviance residuals plots (McCullangh and Nelder, 1989) for Normal Location Model. If $\frac{D}{df}$ are greater than 1, the deviance residuals plots can be used to check if the data is overdispersed or lack of fit.

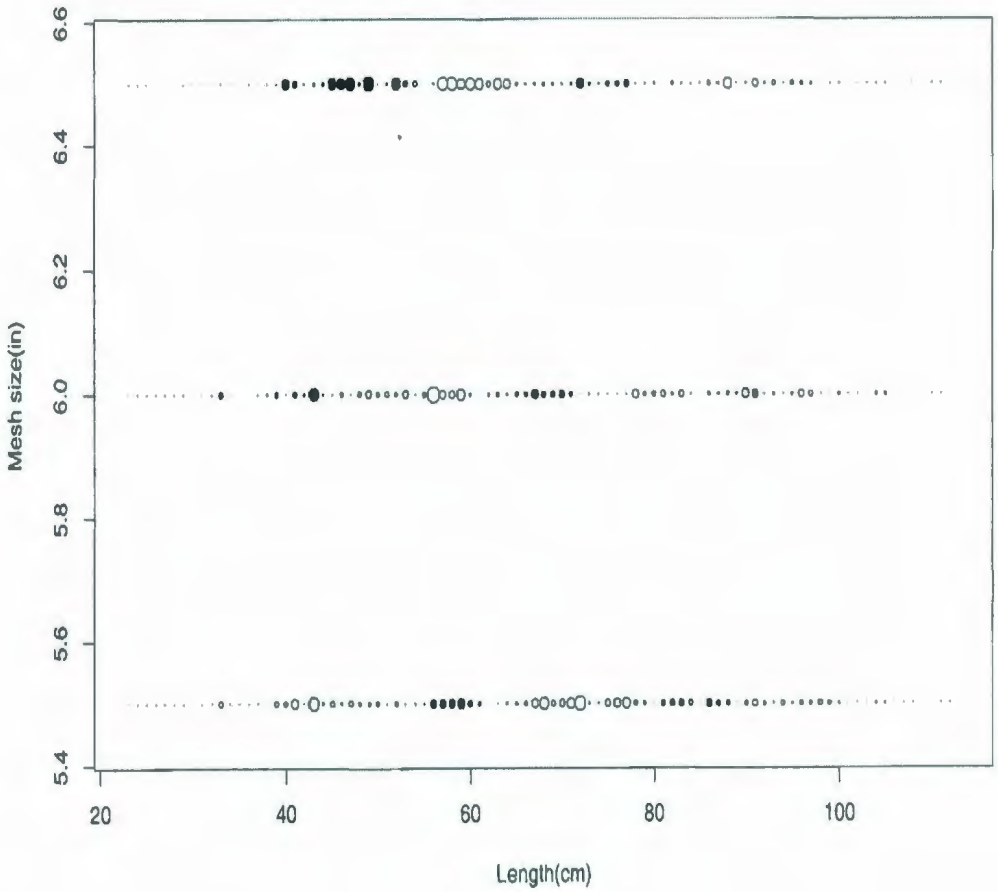

Figure 4.19: Deviance Residuals of Lognormal (mesh1) for EW

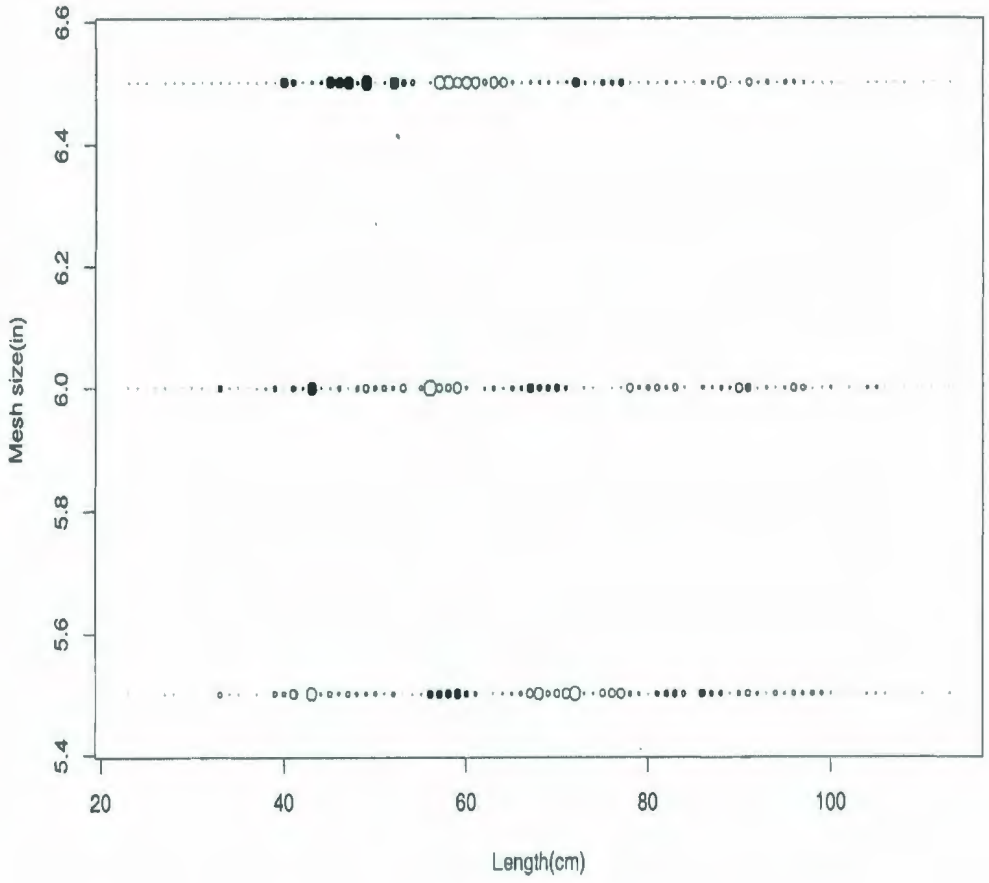

Figure 4.20: Deviance Residuals of Lognormal (mesh2) for EW

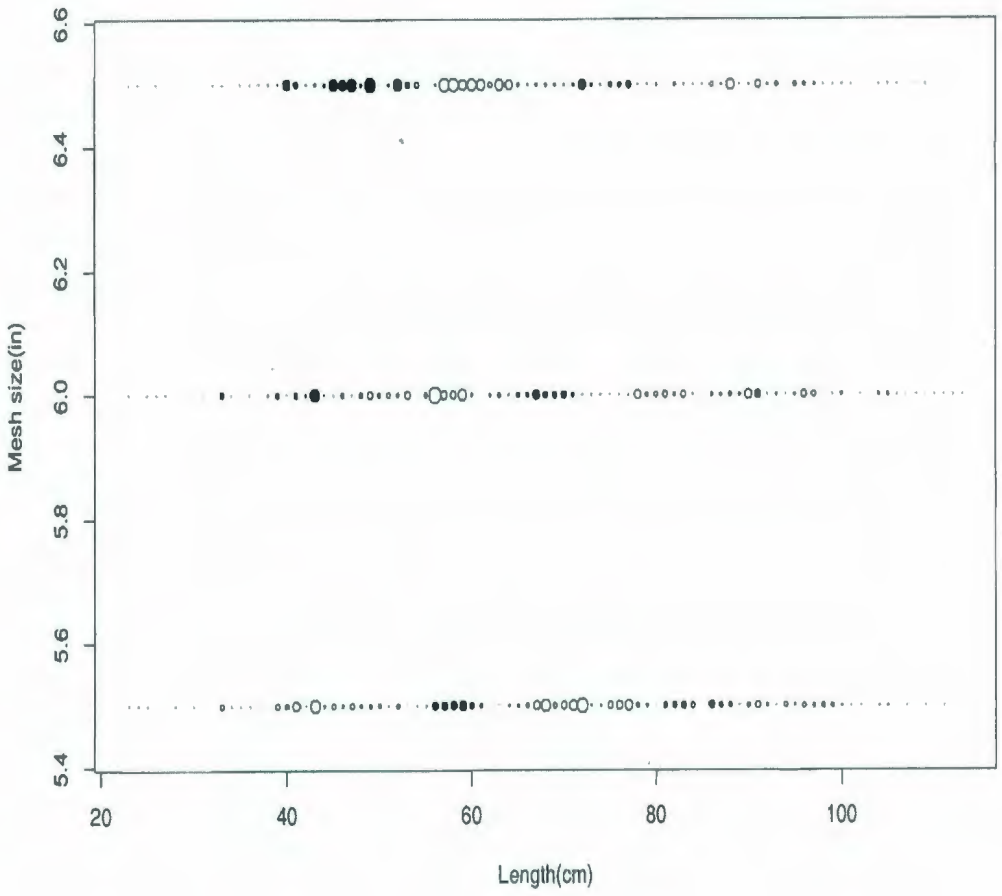

Figure 4.21: Deviance Residuals of Lognormal (mesh3) for EW

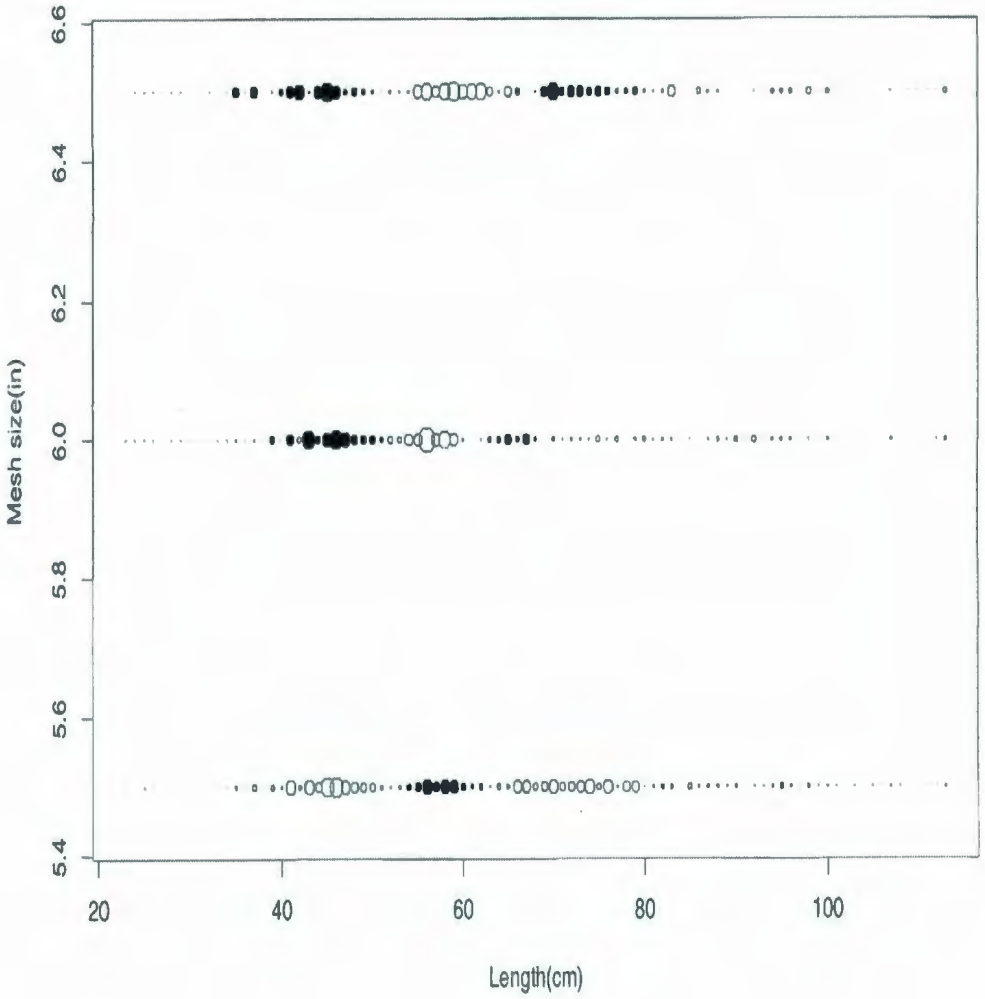

Figure 4.22: Deviance Residuals of Lognormal (mesh1) for JV

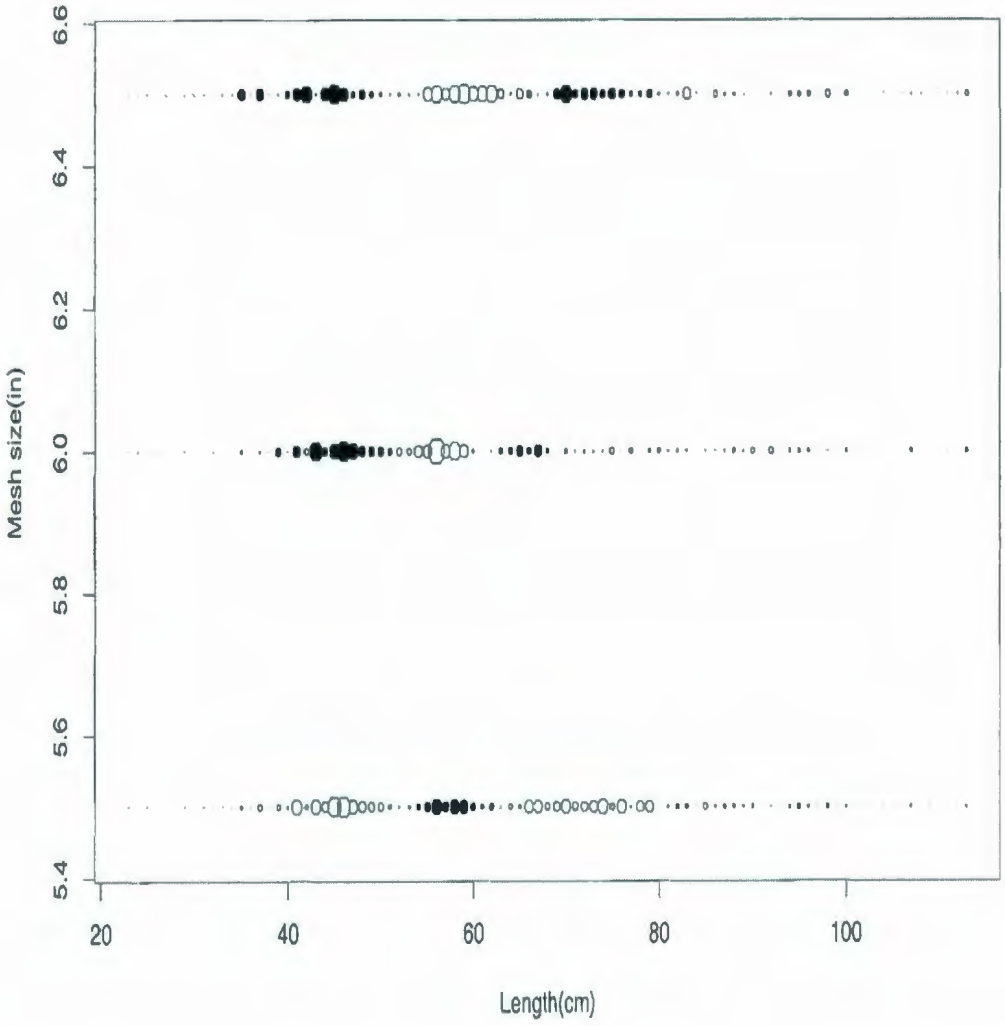

Figure 4.23: Deviance Residuals of Lognormal (mesh2) for JV

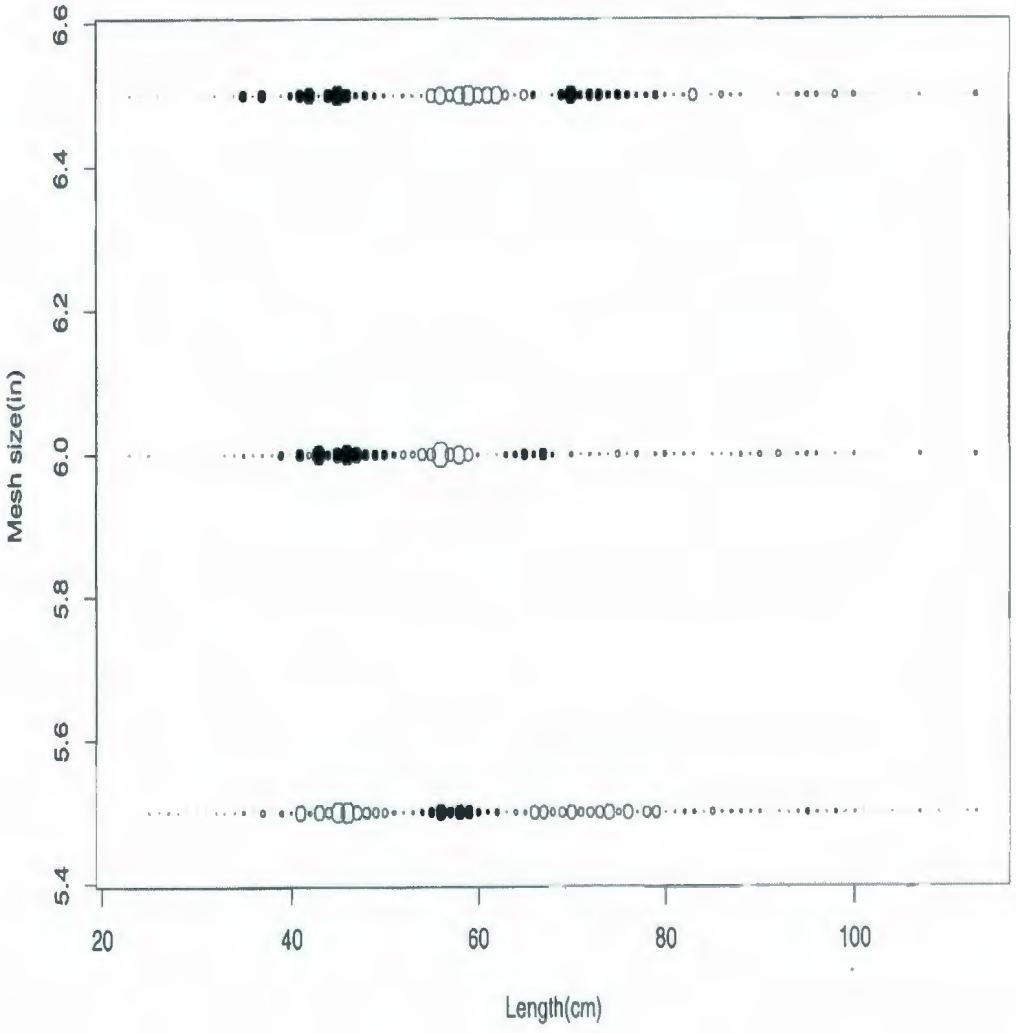

Figure 4.24: Deviance Residuals of Lognormal (mesh3) for JV

From the above deviance residuals plots (McCullangh and Nelder, 1989), we can find there is indeed lack of fit.

Finally, we can get plot of selection curve, which is a convenient presentation of the overall fit. Plot of selection curve gives a quick and qualitative impression of the fit, that is an intuitive assessment of its plausibility. And plots of selection curve are more of visual interest rather than an actual quantitative justification.

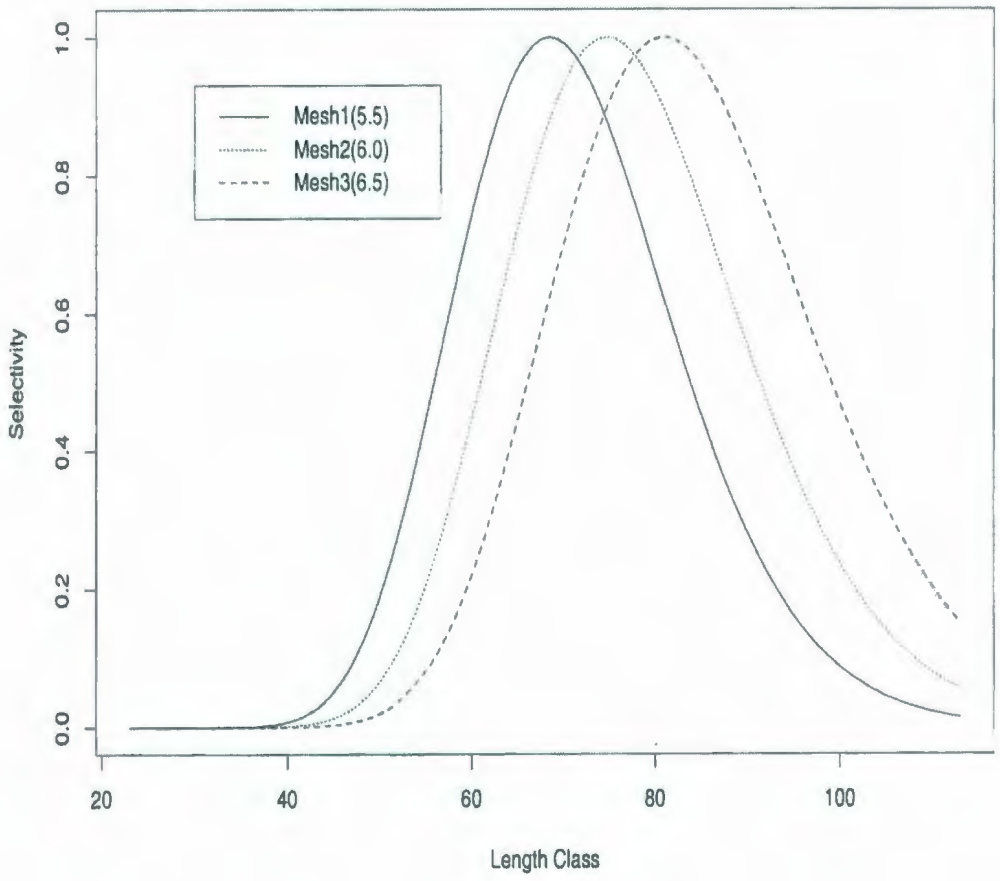

Figure 4.25: EW Lognormal Selection Curves

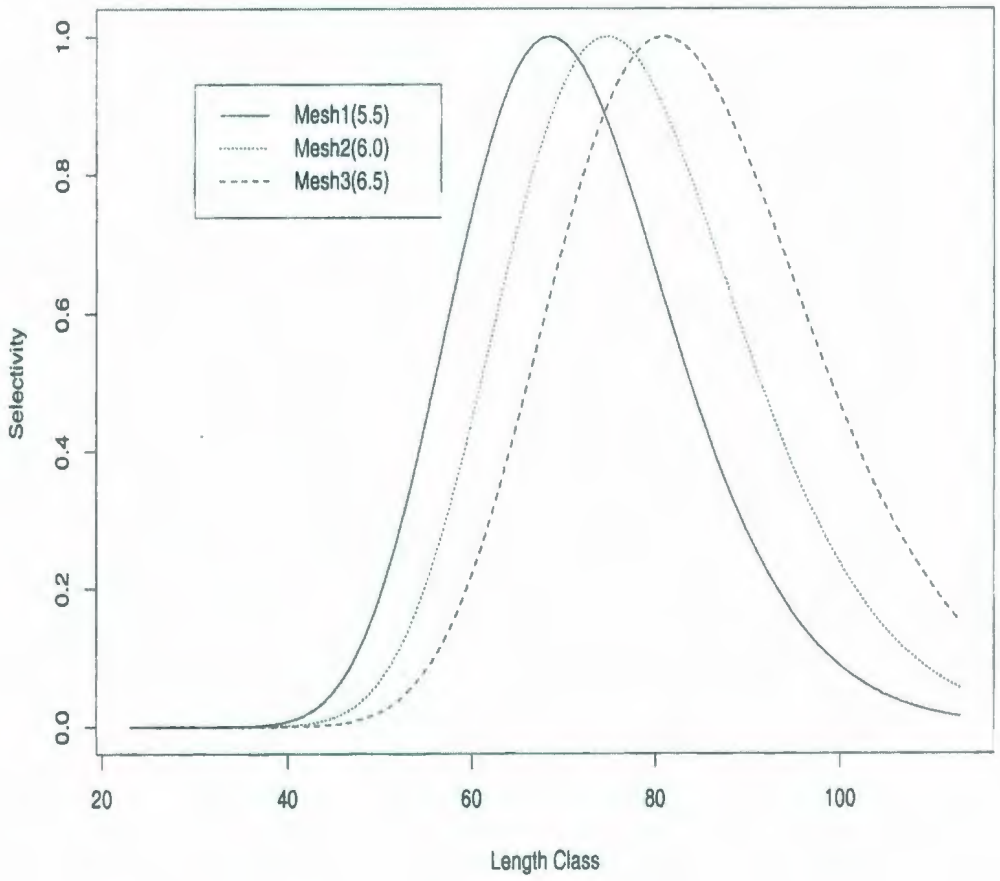

Figure 4.26: JV Lognormal Selection Curves

Gamma Model

Firstly, we can get plots of fitted catch for Gamma Model.

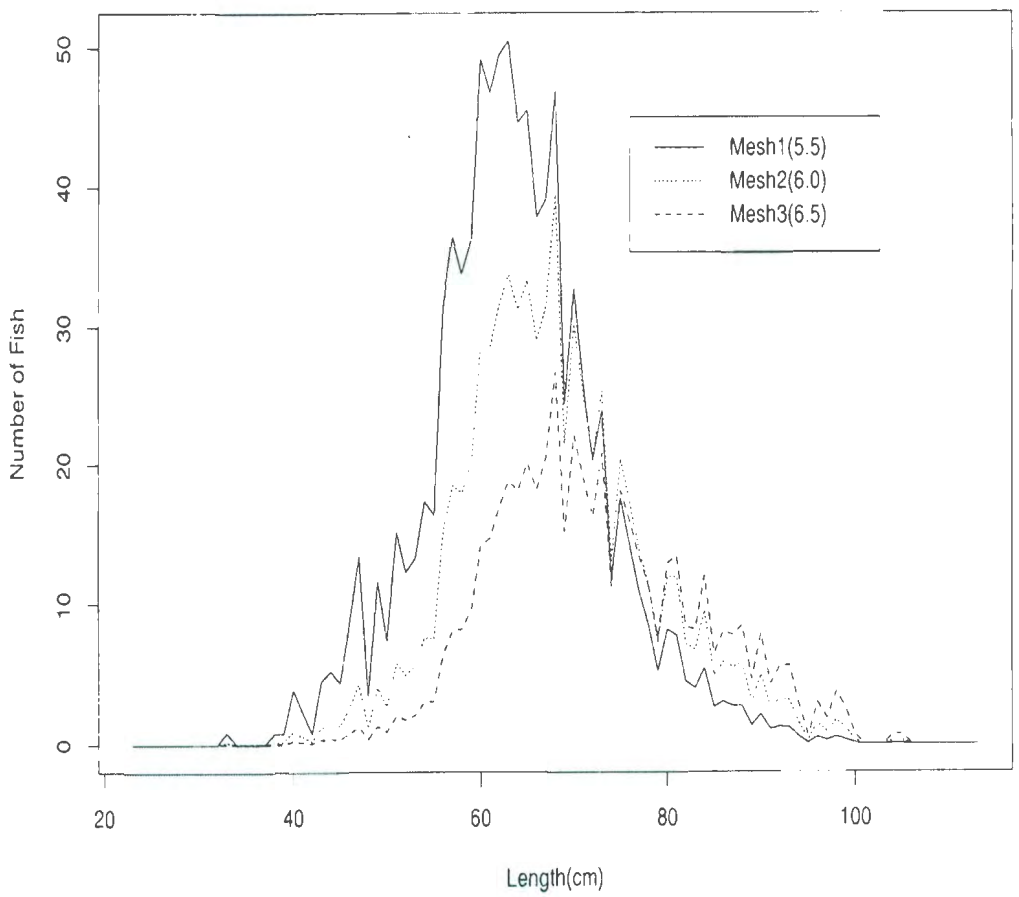

Figure 4.27: EW Gamma Fitted Catch

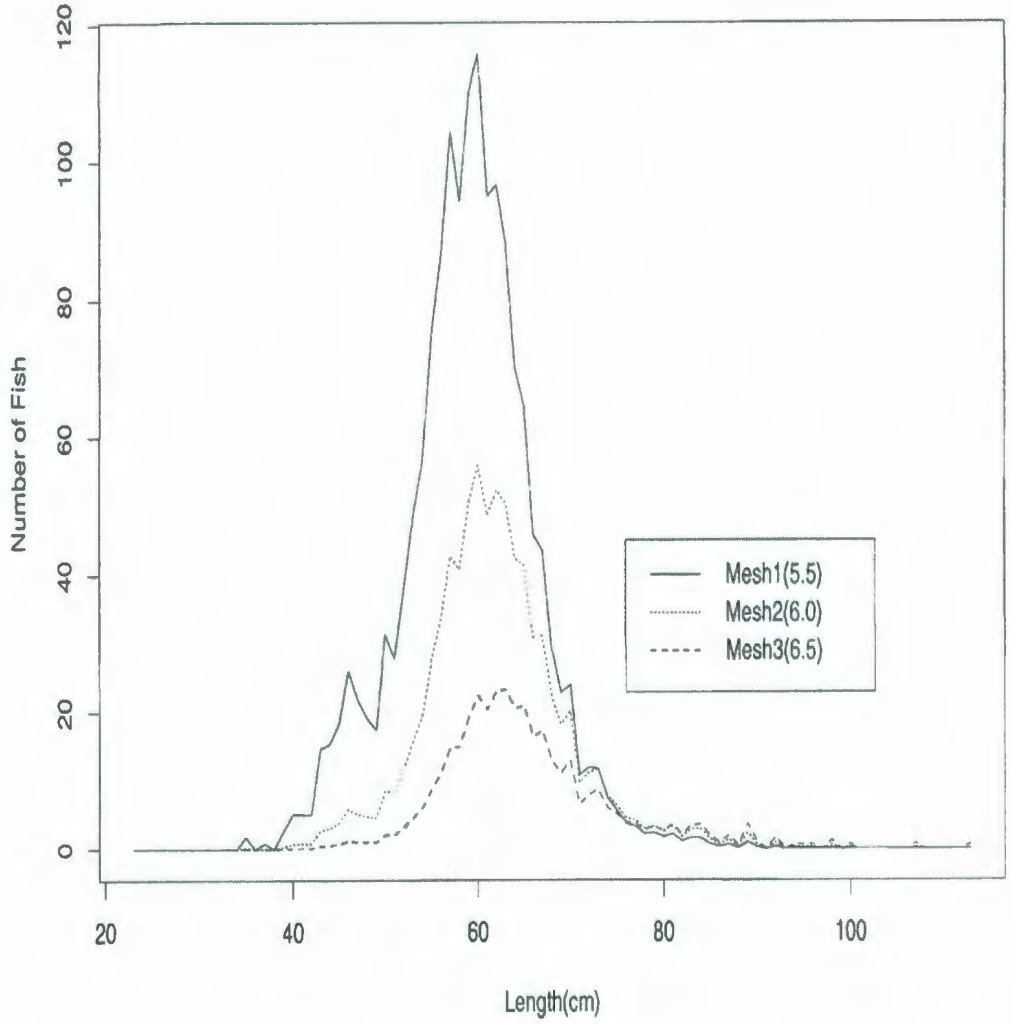

Figure 4.28: JV Gamma Fitted Catch

Secondly, we can get deviance residuals plots (McCullangh and Nelder, 1989) for Normal Location Model. If $\frac{D}{df}$ are greater than 1, the deviance residuals plots can be used to check if the data is overdispersed or lack of fit.

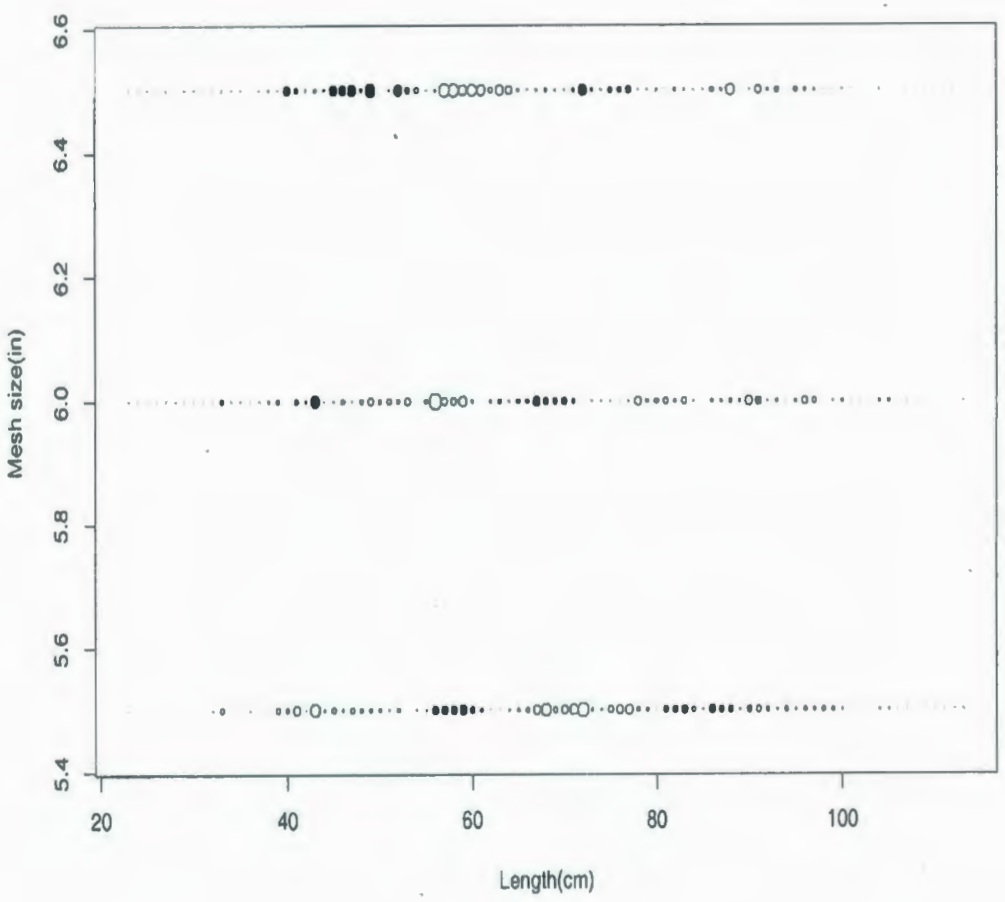

Figure 4.29: Deviance Residuals of Gamma for EW

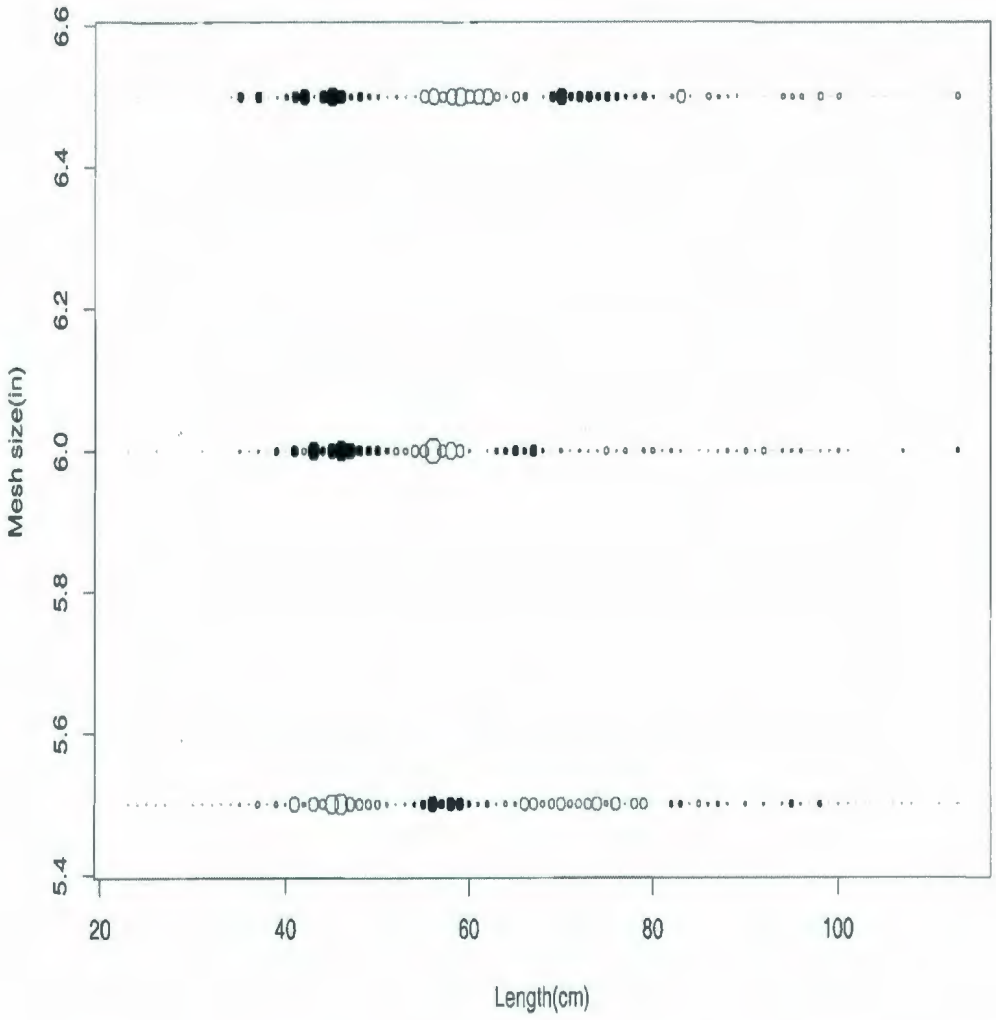

Figure 4.30: Deviance Residuals of Gamma for JV

From the above deviance residuals plots (McCullangh and Nelder, 1989), we can find there is indeed lack of fit.

Finally, we can get plot of selection curve, which is a convenient presentation of the overall fit. Plot of selection curve gives a quick and qualitative impression of the fit, that is an intuitive assessment of its plausibility. And plots of selection curve are more of visual interest rather than an actual quantitative justification.

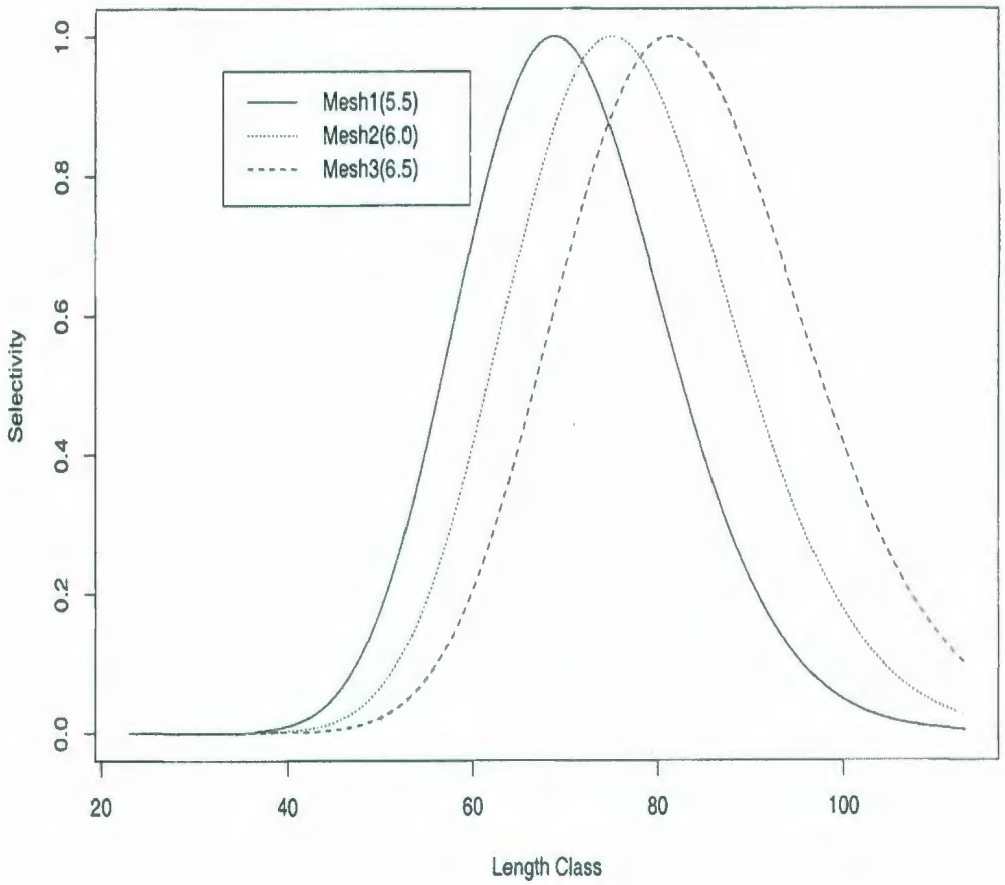

Figure 4.31: EW Gamma Selection Curves

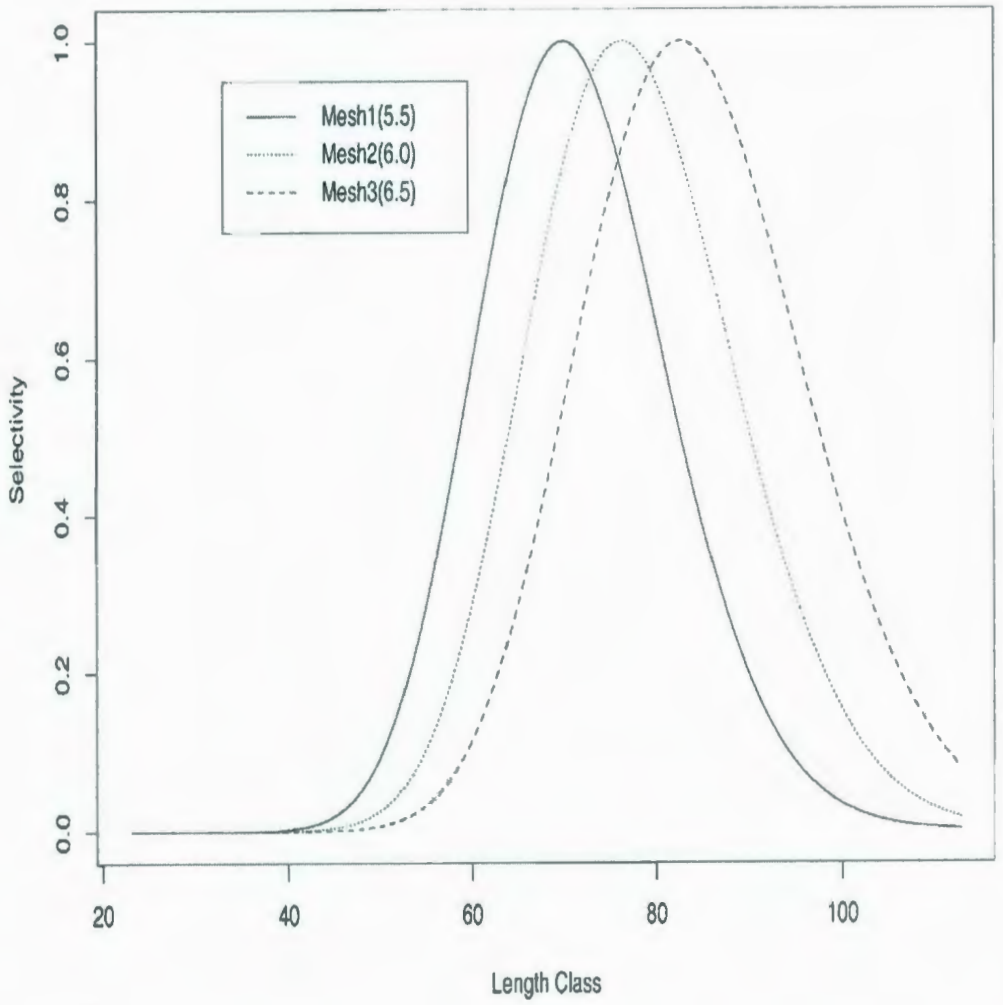

Figure 4.32: JV Gamma Selection Curves

The results of the data fitted by the respective five models are given in Table 2 and Table 3

4.3 Conclusion

It is seen that the normal scale model produces the smallest deviance,617.86, for Jv, but not significantly smaller than the normal location model. For EW, the normal location model produces the smallest deviance,421.86, but not significantly smaller than the normal scale model. For both data set, the Lognormal model yields the largest deviance.

Bibliography

[1] Boy,V., and Crivelli, A. J. *Simultaneous determination of gillnet selectivity and population age-class distribution for two cyprinids* Fisheries Research(1988).

[2] Department of Fisheries and Oceans, Ottawa, Ontario (Canada),Responsible Fishing Operations. Manual for gillnet selectivity(1996).

[3] Hamley, J. A. *Review of gillnet selectivity* Journal of the Fisheries Research Board of Canada(1975).

[4] Helser, T. E., Condrey, R. E., and Geaghan, J. P. *A new method of estimating gillnet selectivity, with an example for spotted seatrout* Canadian Journal of Fisheries and Aquatic Sciences(1991).

[5] Helser, T. E., Geaghan, J. P., and Condrey, R. E. *Estimating size composition and associated variances of a fish population from gillnet selectivity, with an example for spotted seatrout* Fisheries Research(1994).

[6] Henderson, B. A., and Wong, J. L. *A method for estimating gillnet selectivity of walleye(Stizostedionvitreumvitreum) in multimesh multifilament gill nets in Lake Erie, and its application* Canadian Journal of Fisheries and Aquatic Sciences(1991).

[7] Holt, S. J. *A method for determining gear selectivity and its application* ICNAF Special Publication(1963).

[8] Gulland. *Effort and catch per unit effort* Measurement of Fishing Gear Selectivity(1995).

[9] Kirkwood, G. P., and Walker, T. *Gill net mesh selectivities for Gummy Shark, Mustelusantacticus Günther, taken in south-eastern Austrilian waters* Australian Journal of Marine and Freshwater Research(1995).

[10] McCullagh, P., and Nelder, J, A. Generlized linear models, 2nd edit, Chapman and Hall, London(1989).

[11] Millar, R. B. *Estimating the size-selectivity of fishing gear by condtioning on the total catch* Jouanal of the American Statistical Association(1992).

[12] Reigier, H. A., and Robson, D. S. *Selectivity of gillnets, especially to lake whitefish* Journal of the Fisheries Research Board of Canada(1966).

[13] Russell B. Millar and René Holst. *Estimation of gillnet and hook selectivity using log-linear models* ICES Journal of Marine Science(1997).

[14] Holst R, Madsen N,Moth-Poulsen T, *et al.* Manual for gillnet selectivity(1996).

[15] Wileman, D.A., Ferro, R.S.T, Fonteyne, R. and Millar, R.B. *Manual of methods of measuring the selectivity of towed gears* ICES Coop(1996).

Appendix A

DATA DESCRIPTION

The data used in this thesis consists of two data sets, one data set is the total catch data from fleet EW, the other data set is the total catch from fleet JV. The meshsize is 5.5, 6.0,and 6.5(in), the length classes are from 23 cm to 113 cm with increment 1 cm.

EW	Mesh Sizes		
Length Classes	5.5	6.0	6.5
23	0	0	0
24	0	0	0
25	0	0	0
26	0	0	0
27	0	0	0
28	0	0	0
29	0	0	0
30	0	0	0
31	0	0	0
32	0	0	0
33	0	1	0
34	0	0	0
35	0	0	0
36	0	0	0
37	0	0	0
38	1	0	0
39	0	1	0
40	2	1	1
41	0	2	1
42	1	0	0
43	0	6	0

Table A.1: The catch data from fleet EW 1

EW	Mesh Sizes		
Length Classes	5.5	6.0	6.5
44	4	2	1
45	2	1	3
46	7	1	4
47	9	4	6
48	2	3	0
49	9	1	7
50	5	5	1
51	17	3	3
52	9	3	7
53	14	2	5
54	19	8	1
55	19	5	3
56	45	3	5
57	51	11	1
58	48	11	1
59	53	10	3
60	62	25	5
61	55	29	6
62	49	37	12
63	52	42	9
64	49	35	10

Table A.2: The catch data from fleet EW 2

EW	Mesh Sizes		
Length Classes	5.5	6.0	6.5
65	40	42	17
66	31	37	17
67	26	47	18
68	28	52	33
69	18	30	13
70	22	42	21
71	14	32	24
72	7	21	29
73	21	23	26
74	14	12	10
75	11	20	25
76	7	18	22
77	4	13	21
78	13	5	13
79	8	5	7
80	9	8	16
81	13	7	13
82	9	5	6
83	9	3	7
84	3	11	13
85	3	5	6

Table A.3: The catch data from fleet EW 3

EW	Mesh Sizes		
Length Classes	5.5	6.0	6.5
86	8	4	5
87	6	4	6
88	6	9	2
89	2	2	5
90	5	1	9
91	0	7	1
92	3	3	4
93	2	5	3
94	0	2	3
95	0	1	0
96	0	0	5
97	0	0	3
98	0	2	4
99	0	1	3
100	0	0	1
101	0	0	0
102	0	0	0
103	0	0	0
104	0	0	1
105	0	0	1
106	0	0	0

Table A.4: The catch data from fleet EW 4

EW	Mesh Sizes		
Length Classes	5.5	6.0	6.5
107	0	0	0
108	0	0	0
109	0	0	0
110	0	0	0
111	0	0	0
112	0	0	0
113	0	0	0

Table A.5: The catch data from fleet EW 5

JV	Mesh Sizes		
Length Classes	5.5	6.0	6.5
23	0	0	0
24	0	0	0
25	0	0	0
26	0	0	0
27	0	0	0
28	0	0	0
29	0	0	0
30	0	0	0
31	0	0	0
32	0	0	0
33	0	1	0
34	0	0	0
35	1	0	1
36	0	0	0
37	0	0	1
38	0	0	0
39	1	2	0
40	4	1	1
41	0	4	2
42	3	0	3
43	5	12	1

Table A.6: The catch data from fleet JV 1

JV	Mesh Sizes		
Length Classes	5.5	6.0	6.5
44	8	7	4
45	4	12	7
46	8	19	6
47	10	15	3
48	10	11	4
49	10	10	3
50	22	16	4
51	23	13	2
52	41	7	5
53	54	11	4
54	67	10	5
55	95	15	2
56	121	8	2
57	129	26	7
58	126	20	4
59	142	33	5
60	133	51	10
61	106	50	8
62	112	51	9
63	86	61	15
64	61	53	19

Table A.7: The catch data from fleet JV 2

JV	Mesh Sizes		
Length Classes	5.5	6.0	6.5
65	58	57	12
66	29	40	24
67	28	47	17
68	22	27	15
69	14	18	20
70	12	16	29
71	6	9	12
72	6	9	16
73	5	10	17
74	1	9	11
75	3	3	11
76	0	4	8
77	3	2	6
78	0	3	5
79	0	2	7
80	2	1	4
81	2	3	4
82	3	1	1
83	4	4	0
84	2	3	3
85	0	2	2

Table A.8: The catch data from fleet JV 3

JV	Mesh Sizes		
Length Classes	5.5	6.0	6.5
86	1	1	0
87	2	1	1
88	0	0	1
89	1	3	3
90	1	0	1
91	0	0	0
92	1	0	2
93	0	0	0
94	0	1	0
95	1	0	0
96	0	1	0
97	0	0	0
98	1	1	0
99	0	0	0
100	0	1	0
101	0	0	0
102	0	0	0
103	0	0	0
104	0	0	0
105	0	0	0
106	0	0	0

Table A.9: The catch data from fleet JV 4

JV	Mesh Sizes		
Length Classes	5.5	6.0	6.5
107	0	0	1
108	0	0	0
109	0	0	0
110	0	0	0
111	0	0	0
112	0	0	0
113	0	1	0

Table A.10: The catch data from fleet JV 5

Appendix B

SPLUS SOURCE CODE

```
\#\#the data file $=$ EWSum (913 matrix from Dr. Wang's code)
EW.SUM <- read.table(``EW.SUM.dat", head=T)
cat(`` The Catch Data Set From EW Is:")
Print(EW.SUM)
msizes <- c(5.5,6.0,6.5)
msizes.rep <- rep(msizes, rep(91.3))
lens <- c(23:113)
lens.rep <- rep(lens, length=91*3)
var1 <- lens.rep*msizes.rep
var2 <- msizes.rep$^ 2$
EW.catch <- c(EW.SUM[,1],EW.SUM[,2],EW.SUM[,3])
legend <- c(``Mesh1(5.5)",``Mesh1(6.0)",``Mesh1(6.5)")

\#\#glm Normal Location model
EW.loc.fit <- glm(EW.catch~ var1 + var2
+as.factor(lens.rep),family=poisson)
x <- EW.loc.fit&coef[c(``var1"),``var2")]
```

```
EW.mean <- -2*msizes*x[2]/x[1]
st.dev <- sqrt(-2*x[2]/(x[1]*x[1]))
cat(''The mean St. Dev. of Normal loc for EW is:")
print(EW.mean)
print(st.dev)

\#\#observation curve for Ew
postscript(''EW.obs.ps")
par(mfrow=c(1,1))
plot(lens, EW.SUM[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(EW.SUM)), ylab=''Number of Fish",
     main=''EW Observation Catch", type=''l", lty=1)
     for(j in 2: dim(EW.SUM)[2])\{lines(lens, EW.SUM[,j],lty=j)\}
legend(80, 50, legend =legend, lty=1:3)
graphics.off()

\#\#normal location curve
postscript(''EW.loc.ps")
par(mfrow=c(1,1))
Floor <- floor(min(EW.mean - 3* st.dev))
Ceiling <- ceiling(max(EW.mean + 3* st.dev))
XX <- matrix(0, 100, dim(EW.SUM)[2])
for (i in 1: dim(EW.SUM)[2]) {
XX[,i] <- seq(23, 113, length=100)
  }
plot(XX[,1], sqrt(2*pi)* st.dev*dnorm(XX[,1],
        EW.mean[1], st.dev), type=''l", lty=1,
```

```
        xlim=c(23, 113), ylim=c(0,1.0),
        xlab=''Length Class", ylab=''Selectivity",
        main=''EW Selection Location Curves")
for(i in 2:dim(EW.SUM)[2]) { lines(XX[,i], sqrt(2*pi))* st.dev
   *dnorm(XX[,i], EW.mean[i], st.dev), lty=i}
Legend(90, 0.87, legend =Legend, lty=1:3)
graphics.off()

\#\#Residual matrix for normal location
EW.loc.res <- round(matrix(resid(EW.loc.fit,type=''deviance"), 91, 3), dig=4)
EW.loc.res.tab <- round(matrix(resid(EW.loc.fit,type=''deviance"), 91, 3), dig=3)
cat(''The Residuals for Location Model of is: ")
print(EW.loc.res.tab)
postscript(''EW.loc.res.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of Location for EW", type=''n")
   for(i in 1:nrow(EW.SUM))
   for(j in 1:ncol(EW.SUM))
   points(lens[i].msizes[j],pch=ifelse(EW.loc.res[i,j]>0,16,1),
                          mkh=abs(EW.loc.res[i,j])*3/100)
graphics.off()

\#\#fitted curve for normal location
```

```
EW.loc.pred <- predict(EW.loc.fit)
EW.loc.pred <- exp(EW.loc.pred)
EW.loc.pred <- matrix(EW.loc.pred,91,3)
EW.loc.pred.tab <- round(EW.loc.pred, dig=0)
cat("\\n\\nThe fitted Catch for Location Model of EW is: \\n")
print(EW.loc.pred.tab)
postscript("EW.loc.fit.ps")
par(mfrow=c(1,1))
plot(lens, EW.loc.pred[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(EW.loc.pred)), ylab=''Number of Fish",
     main=''EW Normal location Fitted Catch", type="l", lty=1)
     for(j in 2:ncol(EW.SUM))\{
     lines(lens, EW.loc.pred[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)

graphics.off()

\#\#clean jobs for normal location
rm(var1,var2,EW.mean,st.dev,x,EW.loc.fit,XX,Floor,Ceiling)
rm(EW.loc.res)
rm(EW.loc.pred)
rm(EW.loc.res.tab,EW.loc.pred.tab)

\#\#normal scale model
var1 <- lens.rep/msizes.rep
var2 <- msizes.rep$^2$
```

```
\#\#glm Normal scale model
EW.scale.fit <- glm(EW.catch~ var1 + var2
+as.factor(lens.rep),family=poisson)
x <- EW.scale.fit&coef[c(``var1"),``var2")]
EW.mean <- -x[1]*msizes/2*x[2]
st.dev <- -msizes/(2*x[2])

\#\#normal scale curve for EW
postscript(``EW.scale.ps")
par(mfrow=c(1,1))
Floor <- floor(max(23,min(EW.mean - 3* st.dev)))
Ceiling <- ceiling(min(113, max(EW.mean + 3* st.dev)))
XX <- matrix(0, 100, dim(EW.SUM)[2])
for (i in 1: dim(EW.SUM)[2])\{
XX[,i] <- seq(from=(max(23,EW.mean[i]-3*st.dev[i])),
to=(min(113,EW.mean[i]+3*st.dev[i])), length=100)
  \}
plot(XX[,1][XX[,1]> Floor & XX[,1]< Ceiling],
        sqrt(2*pi)* st.dev*dnorm(XX[,1][XX[,1]> Floor & XX[,1]< Ceiling],
        EW.mean[1], st.dev[1]), type=``l", lty=1,
        xlim=c(Floor, Ceiling), ylim=c(0,1.0),
        xlab=``Length Class", ylab=``Selectivity",
        main=``EW Mesh Size Scale Curves")
for(i in 2:dim(EW.SUM)[2]) { lines(XX[,i][XX[,1]> Floor & XX[,1]< Ceiling],
    sqrt(2*pi))* st.dev[i]*dnorm(XX[,i][XX[,1]> Floor & XX[,1]< Ceiling],
    EW.mean[i], st.dev[i]), lty=i}
Legend(29, 0.91, legend =Legend, lty=1:3)
```

```
graphics.off()

\#\#Residual matrix for normal scale
EW.scale.res <- round(matrix(resid(EW.scale.fit,type=''deviance"), 91, 3), dig=4)
EW.scale.res.tab <- round(matrix(resid(EW.scale.fit,type=''deviance"), 91, 3), dig=3)
cat(''The Residuals for Scale Model of EW is: ")
print(EW.Scale.res.tab)
postscript(''EW.scale.res.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of scale for EW", type=''n")
    for(i in 1:nrow(EW.SUM))
    for(j in 1:ncol(EW.SUM))
    points(lens[i].msizes[j],pch=ifelse(EW.scale.res[i,j]>0,16,1),
                          mkh=abs(EW.scale.res[i,j])*3/100)
graphics.off()

\#\#fitted curve for normal scale
EW.scale.pred <- predict(EW.scale.fit)
EW.scale.pred <- exp(EW.scale.pred)
EW.scale.pred <- matrix(EW.scale.pred,91,3)
EW.scale.pred.tab <- round(EW.scale.pred, dig=0)
cat(''The fitted Catch for Scale Model of EW is: ")
print(EW.scale.pred.tab)
```

```
postscript(''EW.scale.fit.ps")
par(mfrow=c(1,1))

plot(lens, EW.scale.pred[,1], xlim=c(min(lens),max(lens)),
xlab=''Length(cm)",
     ylim=c(0,max(EW.scale.pred)), ylab=''Number of Fish",
     main=''EW scale Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(EW.SUM))\{
     lines(lens, EW.scale.pred[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs for normal location
rm(var1,var2,EW.mean,st.dev,x,EW.scale.fit,XX,Floor,Ceiling)
rm(EW.scale.res)
rm(EW.scale.pred)
rm(EW.scale.res.tab,EW.scale.pred.tab)

\#\#Lognormal for three mesh sizes
\#\#for  msizes[1]
rmsizes.rep1 <- msizes.rep/msizes[1]
var11 <- log(lens.rep)*log(rmsizes.rep1) -0.5* (log(rmsizes.rep1))$^2$
var21 <- log(rmsizes.rep1)

\#\#glm for meshsizes[1]
EW.log.fit1 <- glm(EW.catch~ var11 + var21
+as.factor(lens.rep),family=poisson)
```

```
x1 <- EW.log.fit1&coef[c(''var11"),''var21")]
EW.mean1 <- -(1-x1[2])/x1[1]
st.dev1 <- -sqrt(1/x1[1])

\#\#Residual matrix for meshsize1
EW.log.res1 <- round(matrix(resid(EW.log.fit1,type=''deviance"), 91, 3), dig=4)
postscript(''EW.log.res1.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of Lognormal(Mesh1) for EW", type=''n")
     for(i in 1:nrow(EW.SUM))
     for(j in 1:ncol(EW.SUM))
     points(lens[i].msizes[j],pch=ifelse(EW.log.res1[i,j]>0,16,1),
                          mkh=abs(EW.log.res1[i,j])*3/100)
graphics.off()

\#\#fitted curve for meshsize 1
EW.log.pred1 <- predict(EW.log.pred1)
EW.log.pred1 <- exp(EW.log.pred1)
EW.log.pred1 <- matrix(EW.log.pred1,91,3)
postscript(''EW.log.fit1.ps")
par(mfrow=c(1,1))

plot(lens, EW.log.pred1[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
```

```
    ylim=c(0,max(EW.log.pred1)), ylab=''Number of Fish",
    main=''EW lognormal(Mesh1) Fitted Catch", type=''l", lty=1)
    for(j in 2:ncol(EW.SUM))\{
    lines(lens, EW.log.pred1[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs

rm(x1,var11,var21,rmsizes.rep1,EW.log.fit1,EW.log.res1)

rm(EW.log.pred1)

\#\#for msizes[2]
rmsizes.rep2 <- msizes.rep/msizes[2]
var12 <- log(lens.rep)*log(rmsizes.rep2) -0.5* (log(rmsizes.rep2))$^2$
var22 <- log(rmsizes.rep2)

\#\#glm for meshsizes[2]
EW.log.fit2 <- glm(EW.catch~ var12 + var22 +as.factor(lens.rep),family=poisson)
x2 <- EW.log.fit2&coef[c(''var12"),''var22")]
EW.mean2 <- -(1-x2[2])/x2[1]
st.dev2 <- -sqrt(1/x2[1])

\#\#Residual matrix for meshsize2
EW.log.res2 <- round(matrix(resid(EW.log.fit2,type=''deviance"), 91, 3), dig=4)
postscript("EW.log.res2.ps")
```

```
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of Lognormal(Mesh2) for EW", type=''n")
     for(i in 1:nrow(EW.SUM))
     for(j in 1:ncol(EW.SUM))
     points(lens[i].msizes[j],pch=ifelse(EW.log.res2[i,j]>0,16,1),
                              mkh=abs(EW.log.res2[i,j])*3/100)
graphics.off()

\#\#fitted curve for meshsize 2
EW.log.pred2 <- predict(EW.log.pred2)
EW.log.pred2 <- exp(EW.log.pred2)
EW.log.pred2 <- matrix(EW.log.pred2,91,3)
postscript(''EW.log.fit2.ps")
par(mfrow=c(1,1))
plot(lens, EW.log.pred2[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(EW.log.pred2)), ylab=''Number of Fish",
     main=''EW lognormal(Mesh2) Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(EW.SUM))\{
     lines(lens, EW.log.pred2[,j], lty=j)\}
Legend(76, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs
```

```
rm(x2,var12,var22,rmsizes.rep2,EW.log.fit2,EW.log.res2)
rm(EW.log.pred2)

\#\#for msizes[3]

rmsizes.rep3 <- msizes.rep/msizes[3]
var13 <- log(lens.rep)*log(rmsizes.rep3) -0.5* (log(rmsizes.rep3))$^2$
var23 <- log(rmsizes.rep3)

\#\#glm for meshsizes[3]
EW.log.fit3 <- glm(EW.catch~ var13 + var23 +as.factor(lens.rep),family=poisson)
x3 <- EW.log.fit3&coef[c(''var13"),''var23")]
EW.mean3 <- -(1-x3[2])/x3[1]
st.dev3 <- -sqrt(1/x3[1])

\#\#Residual matrix for meshsize3
EW.log.res3 <- round(matrix(resid(EW.log.fit3,type=''deviance"), 91, 3), dig=4)
postscript(''EW.log.res3.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of Lognormal(Mesh3) for EW", type=''n")
     for(i in 1:nrow(EW.SUM))
     for(j in 1:ncol(EW.SUM))
     points(lens[i].msizes[j],pch=ifelse(EW.log.res3[i,j]>0,16,1),
```

```
                        mkh=abs(EW.log.res3[i,j])*3/100)
graphics.off()

\#\#fitted curve for meshsize 3
EW.log.pred3 <- predict(EW.log.pred3)
EW.log.pred3 <- exp(EW.log.pred3)
EW.log.pred3 <- matrix(EW.log.pred3,91,3)
postscript(''EW.log.fit3.ps")
par(mfrow=c(1,1))
plot(lens, EW.log.pred3[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(EW.log.pred3)), ylab=''Number of Fish",
     main=''EW lognormal(Mesh3) Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(EW.SUM))\{
     lines(lens, EW.log.pred3[,j], lty=j)\}
Legend(76, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs
rm(x3,var13,var23,rmsizes.rep3,EW.log.fit3,EW.log.res3)
rm(EW.log.pred3)

\#\#lognormal selectivity curve
EW.mean <- c(EW.mean1, EW.mean2, EW.mean3)
st.dev <- c(st.dev1, st.dev2, st.dev3)
postscript(''EW.log.ps")
par(mfrow=c(1,1))
XX <- matrix(0, 100, dim(EW.SUM)[2])
```

```
for (i in 1: dim(EW.SUM)[2])\{
XX[,i] <- seq(from=23, to=113, length=100)
  \}
plot(XX[,1],dlnorm(XX[,1],EW.mean[1], st.dev[1])/max(dlnorm(XX[,1],
EW.mean[1], st.dev[1])), type=''l", lty=1,
        xlim=c(23, 113), ylim=c(0,1.0),
        xlab=''Length Class", ylab=''Selectivity",
        main=''EW Mesh Size Lognormal Curves")
for(i in 2:dim(EW.SUM)[2])\ { lines(XX[,i],
    dlnorm(XX[,1],EW.mean[1], st.dev[1])/max(dlnorm(XX[,1],
    EW.mean[1], st.dev[1])), lty=i)\}
Legend(30, 0.93, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs
rm(EW.mean,EW.mean1,EW.mean2,EW.mean3,st.dev1)
rm(st.dev2,st.dev3,st.dev,XX,Floor,Ceiling)

\#\#Gamma model
var1 <- log(lens.rep/msizes.rep)
var2 <- lens.rep/msizes.rep

\#\#glm Gamma model
EW.gamma.fit <- glm(EW.catch~ var1 + var2
+as.factor(lens.rep),family=poisson)
x <- EW.gamma.fit&coef[c(''var1"),''var2")]
alpha <- 1 + x[1]
```

```
beta <- -msizes/x[2]

\#\#Residual matrix for gamma
EW.gamma.res <- round(matrix(resid(EW.gamma.fit,type=''deviance"), 91, 3), dig=4)
EW.gamma.res.tab <- round(matrix(resid(EW.gamma.fit,type=''deviance"), 91, 3), dig=3)
cat(''The Residuals for Gamma Model of EW is: ")
print(EW.gamma.res.tab)
postscript("EW.gamma.res.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of gamma for EW", type=''n")
     for(i in 1:nrow(EW.SUM))
     for(j in 1:ncol(EW.SUM))
     points(lens[i].msizes[j],pch=ifelse(EW.gamma.res[i,j]>0,16,1),
                          mkh=abs(EW.gamma.res[i,j])*3/100)
graphics.off()

\#\#gamma curve for Ew
postscript(''EW.gamma.ps")
par(mfrow=c(1,1))
XX <- matrix(0, 1000, dim(EW.SUM)[2])
for (i in 1: dim(EW.SUM)[2])\{
XX[,i] <- seq(from=23, to=113, length=1000)
  \}
```

```
plot(XX[,1],dgamma([XX,1],alpha,1/beta[1])/max(dgamma([XX,1],alpha,1/beta[1])),
        type=''l", lty=1,
        xlim=c(23, 113), ylim=c(0,1.0),
        xlab=''Length Class", ylab=''Selectivity",
        main=''EW Mesh Size Gamma Curves")
for(i in 2:dim(EW.SUM)[2]) \{ lines(XX[,i],
    dgamma([XX,i],alpha,1/beta[1])/max(dgamma([XX,1],alpha,1/beta[1])),
    lty=i\}
Legend(33, 0.95, legend =Legend, lty=1:3)
graphics.off()

\#\#fitted curve for gamma
EW.gamma.pred <- predict(EW.gamma.fit)
EW.gamma.pred <- exp(EW.gamma.pred)
EW.gamma.pred <- matrix(EW.gamma.pred,91,3)
EW.gamma.pred.tab <- round(EW.gamma.pred, dig=0)
cat(''The fitted Catch for Gamma Model of EW is: ")
print(EW.gamma.pred.tab)
postscript(''EW.gamma.fit.ps")
par(mfrow=c(1,1))
plot(lens, EW.gamma.pred[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(EW.gamma.pred)), ylab=''Number of Fish",
     main=''EW gamma Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(EW.SUM))\{
     lines(lens, EW.gamma.pred[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)
graphics.off()
```

```
\#\#clean jobs for gamma
rm(var1,var2,alpha,beta,x,EW.gamma.fit,XX,Floor,Ceiling)
rm(EW.gamma.res)
rm(EW.gamma.pred)
rm(EW.gamma.res.tab,EW.gamma.pred.tab)

\#\#the data file $=$ JVSum (913 matrix from Dr. Wang's code)

JV.SUM <- read.table(``JV.SUM.dat", head=T)
cat(`` The Catch Data Set From JV Is:")
Print(JV.SUM)
msizes <- c(5.5,6.0,6.5)
msizes.rep <- rep(msizes, rep(91.3))
lens <- c(23:113)
lens.rep <- rep(lens, length=91*3)
var1 <- lens.rep*msizes.rep
var2 <- msizes.rep$^ 2$
JV.catch <- c(JV.SUM[,1],JV.SUM[,2],JV.SUM[,3])
legend <- c(``Mesh1(5.5)",``Mesh1(6.0)",``Mesh1(6.5)")

\#\#glm Normal Location model
JV.loc.fit <- glm(JV.catch~ var1 + var2
+as.factor(lens.rep),family=poisson)
x <- JV.loc.fit&coef[c(``var1"),``var2")]
JV.mean <- -2*msizes*x[2]/x[1]
st.dev <- sqrt(-2*x[2]/(x[1]*x[1]))
```

```
cat(''The mean St. Dev. of Normal loc for JV is:")
print(JV.mean)
print(st.dev)

\#\#observation curve for JV
postscript(''JV.obs.ps")
par(mfrow=c(1,1))
plot(lens, JV.SUM[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(JV.SUM)), ylab=''Number of Fish",
     main=''JV Observation Catch", type=''l", lty=1)
     for(j in 2: dim(JV.SUM)[2])\{lines(lens, JV.SUM[,j],lty=j)\}
legend(80, 50, legend =legend, lty=1:3)
graphics.off()

\#\#normal location curve
postscript(''JV.loc.ps")
par(mfrow=c(1,1))
Floor <- floor(min(JV.mean - 3* st.dev))
Ceiling <- ceiling(max(JV.mean + 3* st.dev))
XX <- matrix(0, 100, dim(JV.SUM)[2])
for (i in 1: dim(JV.SUM)[2]) {
XX[,i] <- seq(23, 113, length=100)
  }
plot(XX[,1], sqrt(2*pi)* st.dev*dnorm(XX[,1],
        JV.mean[1], st.dev), type=''l", lty=1,
        xlim=c(23, 113), ylim=c(0,1.0),
        xlab=''Length Class", ylab=''Selectivity",
```

```
        main=''JV Selection Location Curves")
for(i in 2:dim(JV.SUM)[2]) { lines(XX[,i], sqrt(2*pi))* st.dev
   *dnorm(XX[,i], JV.mean[i], st.dev), lty=i}
Legend(90, 0.87, legend =Legend, lty=1:3)
graphics.off()

\#\#Residual matrix for normal location
JV.loc.res <- round(matrix(resid(JV.loc.fit,type=''deviance"), 91, 3), dig=4)
JV.loc.res.tab <- round(matrix(resid(JV.loc.fit,type=''deviance"), 91, 3), dig=3)
cat(''The Residuals for Location Model of is: ")
print(JV.loc.res.tab)
postscript(''JV.loc.res.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of Location for JV", type=''n")
     for(i in 1:nrow(JV.SUM))
     for(j in 1:ncol(JV.SUM))
     points(lens[i].msizes[j],pch=ifelse(JV.loc.res[i,j]>0,16,1),
                          mkh=abs(JV.loc.res[i,j])*3/100)
graphics.off()

\#\#fitted curve for normal location
JV.loc.pred <- predict(JV.loc.fit)
JV.loc.pred <- exp(JV.loc.pred)
```

```
JV.loc.pred <- matrix(JV.loc.pred,91,3)
JV.loc.pred.tab <- round(JV.loc.pred, dig=0)
cat("\\n\\nThe fitted Catch for Location Model of JV is: \\n")
print(JV.loc.pred.tab)
postscript("JV.loc.fit.ps")
par(mfrow=c(1,1))
plot(lens, JV.loc.pred[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(JV.loc.pred)), ylab=''Number of Fish",
     main=''JV Normal location Fitted Catch", type="l", lty=1)
     for(j in 2:ncol(JV.SUM))\{
     lines(lens, JV.loc.pred[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs for normal location
rm(var1,var2,JV.mean,st.dev,x,JV.loc.fit,XX,Floor,Ceiling)
rm(JV.loc.res)
rm(JV.loc.pred)
rm(JV.loc.res.tab,JV.loc.pred.tab)

\#\#normal scale model
var1 <- lens.rep/msizes.rep
var2 <- msizes.rep$^2$

\#\#glm Normal scale model
JV.scale.fit <- glm(JV.catch~ var1 + var2
+as.factor(lens.rep),family=poisson)
```

```
x <- JV.scale.fit&coef[c(''var1"),''var2")]
JV.mean <- -x[1]*msizes/2*x[2]
st.dev <- -msizes/(2*x[2])

\#\#normal scale curve for JV
postscript(''JV.scale.ps")
par(mfrow=c(1,1))
Floor <- floor(max(23,min(JV.mean - 3* st.dev)))
Ceiling <- ceiling(min(113, max(JV.mean + 3* st.dev)))
XX <- matrix(0, 100, dim(JV.SUM)[2])
for (i in 1: dim(JV.SUM)[2])\{
XX[,i] <- seq(from=(max(23,JV.mean[i]-3*st.dev[i])),
to=(min(113,JV.mean[i]+3*st.dev[i])), length=100)
  \}
plot(XX[,1][XX[,1]> Floor & XX[,1]< Ceiling],
        sqrt(2*pi)* st.dev*dnorm(XX[,1][XX[,1]> Floor & XX[,1]< Ceiling],
        JV.mean[1], st.dev[1]), type=''l", lty=1,
        xlim=c(Floor, Ceiling), ylim=c(0,1.0),
        xlab=''Length Class", ylab=''Selectivity",
        main=''JV Mesh Size Scale Curves")
for(i in 2:dim(JV.SUM)[2]) { lines(XX[,i][XX[,1]> Floor & XX[,1]< Ceiling],
    sqrt(2*pi))* st.dev[i]*dnorm(XX[,i][XX[,1]> Floor & XX[,1]< Ceiling],
    JV.mean[i], st.dev[i]), lty=i}
Legend(29, 0.91, legend =Legend, lty=1:3)
graphics.off()

\#\#Residual matrix for normal scale
```

```
JV.scale.res <- round(matrix(resid(JV.scale.fit,type=''deviance"), 91, 3), dig=4)
JV.scale.res.tab <- round(matrix(resid(JV.scale.fit,type=''deviance"), 91, 3), dig=3)
cat(''The Residuals for Scale Model of JV is: ")
print(JV.Scale.res.tab)
postscript(''JV.scale.res.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
    ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
    ylab=''Mesh size(in)",
    yaxp=c(min(msizes),max(sizes),length(msizes)-1),
    main=''Deviance Residuals of scale for JV", type=''n")
    for(i in 1:nrow(JV.SUM))
    for(j in 1:ncol(JV.SUM))
    points(lens[i].msizes[j],pch=ifelse(JV.scale.res[i,j]>0,16,1),
                        mkh=abs(JV.scale.res[i,j])*3/100)
graphics.off()

\#\#fitted curve for normal scale
JV.scale.pred <- predict(JV.scale.fit)
JV.scale.pred <- exp(JV.scale.pred)
JV.scale.pred <- matrix(JV.scale.pred,91,3)
JV.scale.pred.tab <- round(JV.scale.pred, dig=0)
cat(''The fitted Catch for Scale Model of JV is: ")
print(JV.scale.pred.tab)
postscript(''JV.scale.fit.ps")
par(mfrow=c(1,1))
plot(lens, JV.scale.pred[,1], xlim=c(min(lens),max(lens)),
```

```
xlab=''Length(cm)",
     ylim=c(0,max(JV.scale.pred)), ylab=''Number of Fish",
     main=''JV scale Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(JV.SUM))\{
     lines(lens, JV.scale.pred[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs for normal location
rm(var1,var2,JV.mean,st.dev,x,JV.scale.fit,XX,Floor,Ceiling)
rm(JV.scale.res)
rm(JV.scale.pred)
rm(JV.scale.res.tab,JV.scale.pred.tab)

\#\#Lognormal for three mesh sizes
\#\#for  msizes[1]
rmsizes.rep1 <- msizes.rep/msizes[1]
var11 <- log(lens.rep)*log(rmsizes.rep1) -0.5* (log(rmsizes.rep1))$^2$
var21 <- log(rmsizes.rep1)

\#\#glm for meshsizes[1]
JV.log.fit1 <- glm(JV.catch~ var11 + var21
+as.factor(lens.rep),family=poisson)
x1 <- JV.log.fit1&coef[c(''var11"),''var21")]
JV.mean1 <- -(1-x1[2])/x1[1]
st.dev1 <- -sqrt(1/x1[1])
```

```
\#\#Residual matrix for meshsize1
JV.log.res1 <- round(matrix(resid(JV.log.fit1,type=''deviance"), 91, 3), dig=4)
postscript(''JV.log.res1.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of Lognormal(Mesh1) for JV", type=''n")
     for(i in 1:nrow(JV.SUM))
     for(j in 1:ncol(JV.SUM))
     points(lens[i].msizes[j],pch=ifelse(JV.log.res1[i,j]>0,16,1),
                          mkh=abs(JV.log.res1[i,j])*3/100)
graphics.off()

\#\#fitted curve for meshsize 1
JV.log.pred1 <- predict(JV.log.pred1)
JV.log.pred1 <- exp(JV.log.pred1)
JV.log.pred1 <- matrix(JV.log.pred1,91,3)
postscript(''JV.log.fit1.ps")
par(mfrow=c(1,1))
plot(lens, JV.log.pred1[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(JV.log.pred1)), ylab=''Number of Fish",
     main=''JV lognormal(Mesh1) Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(JV.SUM))\{
     lines(lens, JV.log.pred1[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)
```

```
graphics.off()

\#\#clean jobs
rm(x1,var11,var21,rmsizes.rep1,JV.log.fit1,JV.log.res1)
rm(JV.log.pred1)

\#\#for msizes[2]
rmsizes.rep2 <- msizes.rep/msizes[2]
var12 <- log(lens.rep)*log(rmsizes.rep2) -0.5* (log(rmsizes.rep2))$^2$
var22 <- log(rmsizes.rep2)

\#\#glm for meshsizes[2]
JV.log.fit2 <- glm(JV.catch~ var12 + var22 +as.factor(lens.rep),family=poisson)
x2 <- JV.log.fit2&coef[c(''var12"),''var22")]
JV.mean2 <- -(1-x2[2])/x2[1]
st.dev2 <- -sqrt(1/x2[1])

\#\#Residual matrix for meshsize2
JV.log.res2 <- round(matrix(resid(JV.log.fit2,type=''deviance"), 91, 3), dig=4)
postscript("JV.log.res2.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of Lognormal(Mesh2) for JV", type=''n")
     for(i in 1:nrow(JV.SUM))
```

```
     for(j in 1:ncol(JV.SUM))
     points(lens[i].msizes[j],pch=ifelse(JV.log.res2[i,j]>0,16,1),
                          mkh=abs(JV.log.res2[i,j])*3/100)
graphics.off()

\#\#fitted curve for meshsize 2
JV.log.pred2 <- predict(JV.log.pred2)
JV.log.pred2 <- exp(JV.log.pred2)
JV.log.pred2 <- matrix(JV.log.pred2,91,3)
postscript(``JV.log.fit2.ps")
par(mfrow=c(1,1))
plot(lens, JV.log.pred2[,1], xlim=c(min(lens),max(lens)), xlab=``Length(cm)",
     ylim=c(0,max(JV.log.pred2)), ylab=``Number of Fish",
     main=``JV lognormal(Mesh2) Fitted Catch", type=``l", lty=1)
     for(j in 2:ncol(JV.SUM))\{
     lines(lens, JV.log.pred2[,j], lty=j)\}
Legend(76, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs
rm(x2,var12,var22,rmsizes.rep2,JV.log.fit2,JV.log.res2)
rm(JV.log.pred2)

\#\#for msizes[3]
rmsizes.rep3 <- msizes.rep/msizes[3]
var13 <- log(lens.rep)*log(rmsizes.rep3) -0.5* (log(rmsizes.rep3))$^2$
var23 <- log(rmsizes.rep3)
```

```
\#\#glm for meshsizes[3]
JV.log.fit3 <- glm(JV.catch~ var13 + var23 +as.factor(lens.rep),family=poisson)
x3 <- JV.log.fit3&coef[c(``var13"),``var23")]
JV.mean3 <- -(1-x3[2])/x3[1]
st.dev3 <- -sqrt(1/x3[1])

\#\#Residual matrix for meshsize3
JV.log.res3 <- round(matrix(resid(JV.log.fit3,type=``deviance"), 91, 3), dig=4)
postscript(``JV.log.res3.ps")
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=``Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=``Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=``Deviance Residuals of Lognormal(Mesh3) for JV", type=``n")
     for(i in 1:nrow(JV.SUM))
     for(j in 1:ncol(JV.SUM))
     points(lens[i].msizes[j],pch=ifelse(JV.log.res3[i,j]>0,16,1),
                          mkh=abs(JV.log.res3[i,j])*3/100)
graphics.off()

\#\#fitted curve for meshsize 3
JV.log.pred3 <- predict(JV.log.pred3)
JV.log.pred3 <- exp(JV.log.pred3)
JV.log.pred3 <- matrix(JV.log.pred3,91,3)
postscript(``JV.log.fit3.ps")
```

```
par(mfrow=c(1,1))
plot(lens, JV.log.pred3[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(JV.log.pred3)), ylab=''Number of Fish",
     main=''JV lognormal(Mesh3) Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(JV.SUM))\{
     lines(lens, JV.log.pred3[,j], lty=j)\}
Legend(76, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs
rm(x3,var13,var23,rmsizes.rep3,JV.log.fit3,JV.log.res3)
rm(JV.log.pred3)

\#\#lognormal selectivity curve
JV.mean <- c(JV.mean1, JV.mean2, JV.mean3)
st.dev <- c(st.dev1, st.dev2, st.dev3)
postscript(''JV.log.ps")
par(mfrow=c(1,1))
XX <- matrix(0, 100, dim(JV.SUM)[2])
for (i in 1: dim(JV.SUM)[2])\{
XX[,i] <- seq(from=23, to=113, length=100)
  \}
plot(XX[,1],dlnorm(XX[,1],JV.mean[1], st.dev[1])/max(dlnorm(XX[,1],
JV.mean[1], st.dev[1])), type=''l", lty=1,
       xlim=c(23, 113), ylim=c(0,1.0),
       xlab=''Length Class", ylab=''Selectivity",
       main=''JV Mesh Size Lognormal Curves")
```

```
for(i in 2:dim(JV.SUM)[2])\ { lines(XX[,i],
    dlnorm(XX[,1],JV.mean[1], st.dev[1])/max(dlnorm(XX[,1],
    JV.mean[1], st.dev[1])), lty=i)\}
Legend(30, 0.93, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs
rm(JV.mean,JV.mean1,JV.mean2,JV.mean3,st.dev1)
rm(st.dev2,st.dev3,st.dev,XX,Floor,Ceiling)

\#\#Gamma model
var1 <- log(lens.rep/msizes.rep)
var2 <- lens.rep/msizes.rep

\#\#glm Gamma model
JV.gamma.fit <- glm(JV.catch~ var1 + var2
+as.factor(lens.rep),family=poisson)
x <- JV.gamma.fit&coef[c(''var1"),''var2")]
alpha <- 1 + x[1]
beta <- -msizes/x[2]

\#\#Residual matrix for gamma
JV.gamma.res <- round(matrix(resid(JV.gamma.fit,type=''deviance"), 91, 3), dig=4)
JV.gamma.res.tab <- round(matrix(resid(JV.gamma.fit,type=''deviance"), 91, 3), dig=3)
cat(''The Residuals for Gamma Model of JV is: ")
print(JV.gamma.res.tab)
postscript("JV.gamma.res.ps")
```

```
par(mfrow=c(1,1))
plot(lens.rep, msizes.rep, xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(min(msizes),max(msizes))+(3/50)*c(-1,1)*(max(msizes)-min(msizes)),
     ylab=''Mesh size(in)",
     yaxp=c(min(msizes),max(sizes),length(msizes)-1),
     main=''Deviance Residuals of gamma for JV", type=''n")
     for(i in 1:nrow(JV.SUM))
     for(j in 1:ncol(JV.SUM))
     points(lens[i].msizes[j],pch=ifelse(JV.gamma.res[i,j]>0,16,1),
                          mkh=abs(JV.gamma.res[i,j])*3/100)
graphics.off()

\#\#gamma curve for JV
postscript(''JV.gamma.ps")
par(mfrow=c(1,1))
XX <- matrix(0, 1000, dim(JV.SUM)[2])
for (i in 1: dim(JV.SUM)[2])\{
XX[,i] <- seq(from=23, to=113, length=1000)
  \}
plot(XX[,1],dgamma([XX,1],alpha,1/beta[1])/max(dgamma([XX,1],alpha,1/beta[1])),
        type=''l", lty=1,
        xlim=c(23, 113), ylim=c(0,1.0),
        xlab=''Length Class", ylab=''Selectivity",
        main=''JV Mesh Size Gamma Curves")
for(i in 2:dim(JV.SUM)[2]) \{ lines(XX[,i],
    dgamma([XX,1],alpha,1/beta[1])/max(dgamma([XX,1],alpha,1/beta[1])),
    lty=i\}
```

```
Legend(33, 0.95, legend =Legend, lty=1:3)
graphics.off()

\#\#fitted curve for gamma
JV.gamma.pred <- predict(JV.gamma.fit)
JV.gamma.pred <- exp(JV.gamma.pred)
JV.gamma.pred <- matrix(JV.gamma.pred,91,3)
JV.gamma.pred.tab <- round(JV.gamma.pred, dig=0)
cat(''The fitted Catch for Gamma Model of JV is: ")
print(JV.gamma.pred.tab)
postscript(''JV.gamma.fit.ps")
par(mfrow=c(1,1))
plot(lens, JV.gamma.pred[,1], xlim=c(min(lens),max(lens)), xlab=''Length(cm)",
     ylim=c(0,max(JV.gamma.pred)), ylab=''Number of Fish",
     main=''JV gamma Fitted Catch", type=''l", lty=1)
     for(j in 2:ncol(JV.SUM))\{
     lines(lens, JV.gamma.pred[,j], lty=j)\}
Legend(78, 45, legend =Legend, lty=1:3)
graphics.off()

\#\#clean jobs for gamma
rm(var1,var2,alpha,beta,x,JV.gamma.fit,XX,Floor,Ceiling)
rm(JV.gamma.res)
rm(JV.gamma.pred)
rm(JV.gamma.res.tab,JV.gamma.pred.tab)
```